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ABSTRACT

A project was organized to understand and identify basic variations in reading ability by its information processing components. Focusing on three major processing levels in reading--word analysis, discourse analysis, and integration of word/discourse analysis--preliminary research identified perceptual and cognitive skill components of reading and formulated techniques for measuring those skills. Based on data from 48 high school students, the measurements and statistical analyses ultimately focused on eight basic components of reading: letter encoding, multiletter encoding, phonemic translation, lexical access, use of context, predictive extrapolation of a discourse representation, sensitivity to topicality in text, and semantic integration of antecedents within a discourse representation. Factor analysis evaluating the model established the relationship of the reading components to conventional reading tests and to other cognitive abilities. Research then was directed at developing a causal model for the interactions among the reading components, yielding a number of alternative interactive theories. The proposed independent effect of automaticity at the word analysis level on discourse processing components was interpreted as supporting a resource sharing model for process interaction. (Sections of this report describe the general theoretical framework of the project, the structural models and the analysis of covariance structures, the componential analysis of reading skills, analysis of component interactions, and the examination of the reading ability construct.) (RL)

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Report No. 4649

A COMPONENTIAL THEORY OF READING SKILLS AND THEIR INTERACTIONS*

John R. Frederiksen

Bolt Beranek and Newman Inc.

Final Report

April 1981

Final Report, Office of Naval Research Contract No. N00014-76-C-0461, Contract Authority Identification Number NR-154-386. John R. Frederiksen, Principal Investigator.

Running Head: Components of Reading

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ERRATUM SHEET

The following corrections should be noted for BBN Report No. 4649, entitled "A Componential Theory of Reading Skills and Their Interactions" by John R. Frederiksen:

Page 68, Line 17 -- Here, the parameters of Λ are related ...

Page 84, Equation 8 --

$$(8) \quad \rho(\underline{t},\underline{s}) = \frac{\sum_{i} \underline{w}_i \underline{v}_i \rho(\underline{y}_i, \underline{y}_i') + \sum\sum_{i \neq j} \underline{w}_i \underline{v}_j \rho(\underline{y}_i, \underline{y}_j)}{[1 + \sum\sum_{i \neq j} \underline{w}_i \underline{w}_j \rho(\underline{y}_i, \underline{y}_j)]^{\frac{1}{2}} [1 + \sum\sum_{i \neq j} \underline{v}_i \underline{v}_j \rho(\underline{y}_i, \underline{y}_j)]^{\frac{1}{2}}}$$

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This research is concerned with understanding and identifying the limits on reading ability imposed by deficiencies in basic information-processing components. During the first two years of this project, the work has identified perceptual and cognitive skill components of reading, and has formulated techniques for measuring those skills. A series of experiments has pinpointed poor readers' deficiencies in perceiving orthographic units, in phonological decoding, in using context in lexical identification, and

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in extrapolating discourse context to activate likely concepts in semantic memory. Other measures have focused on aspects of discourse processing, particularly as they are utilized in understanding anaphoric reference in a text. Studies of the effects of staging of ideas, topicalization, syntactic form, number of available referents, and other text variables on subjects' performance in comprehending anaphoric reference have led to a provisional set of rules used by readers in assigning text referents, and to the beginnings of a theory for discourse processing.

Some 20 measures of these and other processes have been related to eight basic components of reading: letter encoding, multiletter encoding, phonemic translation, lexical access, use of context, predictive extrapolation of a discourse representation, sensitivity to topicality in text, and semantic integration of antecedents within a discourse representation. Confirmatory maximum-likelihood factor analysis has been used to evaluate the model, and established the relationship of reading components to conventional reading tests and to other cognitive abilities.

Research in the final year has been directed at developing a causal model for the interactions among reading components in establishing overall levels of reading performance. Using Jöreskog's ACOVS (Analysis of Covariance Structures) approach, a number of alternative interactive theories have been examined. In the final theory, perceptual skills contribute to efficient (automatic) decoding, which in turn determines efficiency of word recognition. Efficient word recognition is in turn the determining factor in setting the level of efficiency in context utilization; the lower-level perceptual and decoding components are correlated with measures of context utilization only through their effect on efficiency of lexical retrieval. This is not the case for components related to the analysis of discourse. Skill levels in sensitivity to topicality and semantic integration of antecedents are both determined directly by the levels of perceptual/decoding automaticity, as well as by efficiency of word recognition. This independent effect of automaticity at the word analysis level on discourse processing components is interpreted as supporting a resource-sharing model for process interaction.

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ABSTRACT

This research is concerned with understanding and identifying the limits on reading ability imposed by deficiencies in basic information - processing components. During the first two years of this project, the work has identified perceptual and cognitive skill components of reading, and has formulated techniques for measuring those skills. A series of experiments has pinpointed poor readers' deficiencies in perceiving orthographic units, in phonological decoding, in using context in lexical identification, and in extrapolating discourse context to activate likely concepts in semantic memory. Other measures have focused on aspects of discourse processing, particularly as they are utilized in understanding anaphoric reference in a text. Studies of the effects of staging of ideas, topicalization, syntactic form, number of available referents, and other text variables on subjects' performance in comprehending anaphoric reference have led to a provisional set of rules used by readers in assigning text referents, and to the beginnings of a theory for discourse processing.

Some 20 measures of these and other processes have

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Research in the final year has been directed at developing a causal model for the interactions among reading components in establishing overall levels of reading performance. Using Jöreskog´s ACOVS (Analysis of Covariance Structures) approach, a number of alternative interactive theories have been examined. In the final theory, perceptual skills contribute to efficient (automatic) decoding, which in turn determines efficiency of word recognition. Efficient word recognition is in turn the determining factor in setting the level of efficiency in context utilization; the lower-level perceptual and decoding components are correlated with measures of context utilization only through their effect on efficiency of lexical retrieval. This is not the case for components related to the analysis of discourse. Skill levels in sensitivity to topicality and semantic integration of antecedents are both determined directly by the levels of perceptual/decoding automaticity, as well as by efficiency of word recognition. This independent effect of automaticity at the word analysis level on discourse processing components is interpreted as supporting a resource-sharing model for process interaction.

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GENERAL THEORETICAL FRAMEWORK

A componential theory of reading (or of any other complex performance) attempts to identify a set of functionally defined information processing systems or components which, in interaction with one another, accomplish the more complex performance -- in this case, reading with comprehension. Component processes are defined by the types of data structures on which they operate (the _domain_ or _situation_ in which they operate), and by the specific transformations of those data structures that result (the _function_ or _action_ performed). Components can be thought of as corresponding to the production systems of Artificial Intelligence, which consist of situation-action pairs (Winston, 1979, p. 144). Productions (and components) are applied when their triggering situations occur. Their actions alter the internal data structures and therefore set the stage for still other productions. Productions -- and components -- are, in effect, always available for use, and are automatically applied whenever their defining input data structures make an appearance.

An advantage of production system theories is that no executive control processes need be postulated. Components will be applied in sequences that are determined by their pattern of interaction, as it is determined by their joint effects on a common internal data base. Thus, the controls over component operations reside in the specification of the situations in which they are applied. For example, in the theory of reading, a decoding processes is postulated that has as input an orthographic array consisting of encoded letters or multiletter units. This process applies grapheme-phoneme correspondence rules and results in a pronunciation for the input array. The process cannot operate until its input situation occurs -- namely, letters and/or multiletter units have been encoded. There is thus an automatic sequencing of processes for encoding orthographic units and decoding. However, encoding of multiletter units and encoding of individual graphemes both require as input a set of visual features distributed spatially. These two components are, therefore, not sequentially organized.

In a componential theory, readers may be thought of as differing in the degree to which productions, or components, have become automated (cf. Schneider &

Shiffrin, 1977; Shiffrin & Schneider, 1977). Automatic processes can operate concurrently with other components, without degrading their efficiency of operation. In contrast, controlled (nonautomatic) processes make demands on general, shared processing resources; when they must operate concurrently with other processes, performance is degraded. A skilled reader possesses many, highly automated components, while a less skilled reader has a smaller number of such components, and those may be quantitatively less automated. However, the specific components that lack automation may vary considerably within the population of poorly skilled, young adult readers. Thus, while readers may be reliably classified along a single dimension of "general reading ability," the actual sources of low tested ability may vary considerably from reader to reader.

Measurement of Components

A definition of a processing component such as the one we have presented has immediate implications for the measurement, and thus the identification, of components as determiners of readers' performance. The precise specification of a domain of operation allows (a) the selection of a task which invokes the component and (b) the identification of stimulus variables whose manipulation will alter processing difficulty with respect to the designated component. Contrasts among task conditions can then be developed that represent the degree to which performance is degraded as component-specific processing is rendered more difficult. Measures such as these are theory based and thus are susceptible to experimental validation or invalidation. Validity is established by showing that the manipulation of task difficulty has produced the predicted change in performance. Component-specific measures of individual performance are the values of these contrasts obtained for individual subjects.

Example: Encoding multiletter units. Consider, for example, the process of encoding multiletter units. Unit detectors are hypothesized to respond more readily (a) when units are of high frequency within English orthography and (b) when units are in positions where they are normally likely to occur (Mason, 1975; Mason & Katz, 1976). Accordingly, an experiment was carried out testing the effects of these variables on a subject's speed in encoding and reporting multiletter units. The display conditions were arranged to ensure that efficient perceptual processing would be required for task performance while at the same time allowing manipulation of these variables. Stimuli were four-letter items, preceded and followed by a 300 msec pattern mask, allowing an exposure duration of 100 msec. While on a third of trials the items were four-letter, common English words, on the remaining trials, two of the four letters were masked continuously during the exposure, allowing only a single letter pair (a bigram) to be available for encoding. The critical bigrams were of either high or low frequency ($\underline{T}$ > 260 or $\underline{T}$ < 75 in the Mayzner & Tressault, 1965, tables), of high or low positional likelihood (with a priori conditional probabilities of being presented in the tested position, $\underline{P}$[Position/Bigram] > .55 or < .10), and were presented in either the initial, middle, or final position within the array. The subject´s task was to report all letters as soon as possible.

For the least skilled readers (those who scored below the 48th percentile on the Nelson-Denny Reading Test), performance was found to depend upon the frequency and positional likelihood of the stimulus bigrams, as had been predicted. For these subjects, high-frequency bigrams were encoded an average of 41 msec faster than were low-frequency bigrams, and initial bigrams were encoded 39 msec faster when they were likely to appear in that position than when they were unlikely to appear there. Comparable figures for a middle group of readers (scoring between the 48th and 77th percentiles) were 35 msec and 20 msec, while those for a high-ability group (scoring at or above the 85th percentile) were essentially zero -- .3 msec and 4.2 msec. The experimental variables thus had the predicted effects on performance, particularly for those readers who were least likely to have automated perceptual skills for encoding multiletter orthographic units.

When, as in this example, mean performance for the various task conditions has followed the predicted pattern, a second criterion for validation of the component can be applied. This criterion serves the purpose of establishing that individuals differ reliably in measured levels of performance on the given component, even when alternative measurement operations -- that are in theory equivalent -- are employed. In this next step, two or more contrasts among task conditions are chosen that (a) are experimentally independent and (b) produce changes in processing difficulty with respect to the particular component.

These contrasts, calculated for the individual subject, constitute alternative indices of component-specific performance. As such, they must show construct validity; they must be positively correlated with one another (convergent validity), and at the same time show consistent patterns of correlation, or lack of correlation, with measures of other components (discriminant validity). The theory thus generates an explicit hypothesis about the componential complexity or structure for a set of measures, and this hypothesis (termed a measurement model) is amenable to statistical evaluation through the use of confirmatory maximum-likelihood factor analysis.

Overview of Component Skills in Reading

The two methods for validation of component-specific measures -- verifying effects of task manipulations on task difficulty and the analysis of correlations among measures in fitting a measurement model -- have been applied in three major processing areas in reading. In Figure 1 these three major processing levels are described and their interrelations represented. The unit of informational analysis is the single fixation, which makes available for processing a set of words or phrases. At the moment of fixation, the reader has available to apply to the information obtained within the fixation (a) a set of _word analysis processes_, (b) a discourse model generated from previous text by _discourse analysis processes_, and (c) an ability to combine information from word and discourse sources by what we term _integrative processes_. As indicated in the figure, we suggest a set of component processes that constitute each category.

Insert Figure 1 about here

Word Analysis Processes

Word analysis includes processing components involved in the perception of single-letter and multiletter orthographic units, the translation of orthographic information into a phonological representation, the assignment of appropriate speech patterns to such translated units (e.g., stress, pitch, contour), and the depth of processing in retrieving lexical categories. Note that the defining characteristics of these word analysis processes is that they are all limited to processing information available within a single word.

Discourse Analysis Processes

Discourse analysis processes are used for analyzing lexical and structural information at the text level (rather than at the word level) for the purpose of constructing a text model that represents the reader´s understanding. These component processes include retrieving and integrating word meanings, constructing a propositional base (including analysis of noun groups and establishing case relations), analyzing cohesive relations among sentences or propositions, resolving problems of reference (anaphora and cataphora), constructing inferential elaboration of the text structure, and relating the text structure to prior knowledge of the subject matter.

Integrative Processes

At the moment of visual fixation, the reader has available (a) perceptual, phonological, and structural information about lexical items included in the fixation, and (b) semantic, conceptual, and pragmatic knowledge resulting from the analysis of prior discourse. Integrative processes permit the reader to combine information from these multiple sources, yielding a set of lexical identifications for the fixated items. The components of the integrative processes are directly related to the sources of available information. They include the extrapolation of the discourse model in terms of generating semantic-syntactic forms which can be expected to occur in the text to follow, and the utilization of this information -- this pre-activation of nodes within memory -- so as to more readily make lexical identifications. The generative process may, in a skilled reader, resemble the spread of activation postulated by Collins and Loftus (1975). The integrative utilization of perceptual and semantic information requires a mechanism such as the logogen, postulated by Morton (1969).

In Figure 1, we have attempted to show how a capability for integrative processing can lead to improvement in efficiency of processing within both the word analysis and discourse analysis categories. For example, by using semantic constraints, the amount of orthographic encoding and analysis required for word recognition could be reduced, and the tendency to encode in phrasal units could be increased. In addition, success in generating hypotheses regarding semantic-syntactic aspects of future text could increase the reader's confidence in the text model he or she has created. This in turn could lead to an increase in the tendency of the reader to use a sampling strategy and to a decrease in the amount of text required for establishing the adequacy of text analysis.

Forms of Component Interaction

Within or between these processing areas, components can interact by virtue of their effects on the common internal data base and their usage of shared processing resources. Together, these mechanisms provide for a number of functionally determined types of component interaction. These are listed in Table 1.

Insert Table 1 about here

Functionally Determined Component Interactions

Data-linked components. Components can interact by virtue of their operating on a common memory store. For example, two components may require common input information structures, but otherwise operate independently. Such components are linked through correlated input data. Other components may in their operation construct input data structures that are needed by other components. Their operation will thus determine the usage of the later-occurring processes, so that together the components form a processing hierarchy. If two processes run concurrently, but the second process improves in efficiency and quality of output as the first process runs further to completion, the processes are called _cascaded processes_ (cf. McClelland, 1978). If the operation of the second process depends upon data structures created by the first process running to completion (or to some fixed point), the processes are _dependent processes_. Finally, concurrent processes may both operate on a common data store, and if attendant changes in the data store caused by one process facilitate (or otherwise alter) the operation of the other process, then the components are _mutually facilitatory_.

Process-linked components. Components can also interact by virtue of their mutual dependence on the operation of other component processes; such components are termed _process-linked components_. For example, two components might require a common or _shared subprocess_ for their execution. Alternatively, two components might be invoked by a single _shared control process_. (This latter case is formally a special case of processes linked through correlated input data; here, of course, the emphasis is on the third component, which creates the required data structures.)

Resource-linked components. A third form of functional interaction among components occurs when two or more components must compete for common or shared processing resources. Such components are called resource-linked components. Shared resources might include use of a limited-capacity processor, shared memory access/retrieval channels, or limited capacity working memory (cf. Perfetti & Lesgold, 1977; 1979). When two processes are in competition for resources, increases in the automaticity of one process will free resources for the second process.

Each of these types of functional interaction among components constitutes a possible source of correlation among components. If a componential theory of reading is to be complete, it must delineate the forms of interaction among components, and thus account for correlation among measured components. Theories of component interaction -- presented as explicit hypotheses concerning the manner and nature of component interactions within the processing system -- can be stated and evaluated by defining a set of structural equations that account for the links among components. (Bentler, 1980, has provided a clear account of structural equations and their use in psychological theory.) Estimation of parameters of these equations, as well as a test of goodness of fit, are possible through an application of Jöreskog's ACOVS program (Jöreskog, 1970), or by using LISREL (Jöreskog & Sörbom, 1977).

Nonfunctional Sources of Covariation among Components

Beyond the functional sources of component interactions I have been describing, there are other *nonfunctional sources of intercorrelation among components*. These include correlations due to etiological factors -- the circumstances under which processing components are acquired -- and other, biological factors. For example, component reading skills might be sequenced in instruction. Differential access of pupils to effective learning environments would constitute a second etiological source of intercorrelation among components. A third nonfunctional source of process interaction, and probably the most controversial, is the notion of a general, biologically determined propensity for acquiring certain classes of component processes. Evidence for these etiological sources of reading skill will be found in the presence of persistent background correlations among components that remain after specific theoretically hypothesized and functionally determined interactions have been taken into account.

The statistical procedures for analysis of covariance structures allow us to verify the presence or absence of such background correlations, by permitting us to fit alternative structural models that by hypothesis allow or disallow such background covariation. As with any statistical test, the results will permit us to accept or reject the hypothesis of background intercorrelation among components, or they will indicate an inconclusive outcome, one in which either conclusion is defensible.

STRUCTURAL MODELS AND THE ANALYSIS OF COVARIANCE STRUCTURES

Components can be correlated due to any of these functional sources of interaction among processes, or to other nonfunctional, etiological factors. My purpose here is to show how hypotheses concerning component interactions can be represented as a set of structural equations. These equations can be used to generate, in turn, a hypothesized covariance structure falling within the family of models dealt with in Jöreskog's Analysis of Covariance Structures (ACOVS) (Jöreskog, 1970), or LISREL (Jöreskog & Sörbom, 1977).

Since 1965, I have been intrigued with the possibility of using confirmatory maximum-likelihood factor analysis as a tool for testing theories of human cognition. In particular, I have been interested in developing measurement systems whose theoretical underpinnings thoroughly constrain the parameters of the second-order factor model:

(1) $\Sigma = \beta\Lambda\Phi\Lambda'\beta' + \Theta^2$

as presented, for example, by Jöreskog (1970). In this equation, Σ denotes the variance-covariance matrix (usually the correlation matrix) for a set of componentially specific measures. β contains parameters of the measurement model. Each row of β represents a single measure, while the columns correspond to components or, in the older language, factors. A nonzero entry in the ith row and jth column of β indicates that the measure i is, by hypothesis, determined at least in part by the level of skill in component *j*. Matrix Θ^2 is a diagonal matrix, containing unique (or error) variance associated with each of the measures. If we define

$$(2) \quad \Phi^* = \Lambda\Phi\Lambda',$$

equation (1) can be re-written as

$$(3) \quad \Sigma = \beta\Phi^*\beta' + \Theta^2,$$

where Φ^* contains the intercorrelations among the measured components. This equation is that of a first-order factor model and is used in testing a hypothesized measurement model. Equation (2) relates intercorrelations among measured components to parameters of the interactive model. The specification of a structural model for component interactions leads to a series of constraints on the matrix Λ. (How this is done will be described below.) The matrix Φ contains background intercorrelations among components, after removing correlations due to theoretically proscribed component interactions. In summary, each of the matrices in equation (1) corresponds to a different aspect of our problem: the relation of observed variables to components in a measurement model (β), the forms of component interaction as represented by a set of structural equations (Λ), and the presence of background correlations among components (Φ). By constraining parameters within each of these matrices in the general model, one can test these different aspects of the componential theory.

Evaluating the Measurement Model

Fixing parameters of β, while allowing the factors -- measurements of components -- to freely intercorrelate (i.e., by regarding all elements of Φ^* to be free parameters) permits us to test a measurement model. Comparative model fitting is accomplished by varying the hypothesized structure of β. No assumptions about component interactions are necessary at this stage.

Testing Structural Models

Measured performance on a component *j* (η_j) is resolved within the structural equation system into (a) that which is contributed by measured performance on other components (η_k, $k \neq j$), and (b) that which is contributed by *unique* skill on the *j*th component itself (ζ_j). These relationships are expressed in a linear structural equation relating performance on component *j* to each of these contributory sources:

$$(4) \quad \eta_j = \sum_{k \neq j} \delta_{jk} \eta_k + \delta_{jj} \zeta_j$$

where $\delta_{jk} = 0$ if component k does not directly influence performance on component j and $\delta_{jk} \neq 0$ where specific interactions among components are postulated. After specifying the pattern of component interactions -- by specifying j equations of form (4), the resulting set of equations is rewritten so as to express each of the ζ's (the unique components) as a linear function of the η's (the measured components). These equations can then be combined in a single matrix equation:

$$(5)\quad \underline{D}\zeta = \Delta\eta,$$

where $\underline{D}$ is a diagonal matrix whose jth element is δ_{jj}, Δ is a square matrix having diagonal elements 1 and off diagonal elements $-\delta_{jk}$, and ζ and η are random vectors representing unique and measured components, respectively. Since in the factor model of equation (1) measured components must be expressed as linear combinations of unique components, equation (5) must be solved to give:

$$(6)\quad \eta = \Delta^{-1}\underline{D}\zeta = \Lambda\zeta.$$

Thus, the parameters of the structural equation system are related to those of the factor model by the relation $\Lambda = \Delta^{-1}D$. The covariances among the measured components are then given by

$$(7)\quad \underline{E}(\Lambda\zeta\zeta'\Lambda') = \Lambda\underline{E}(\zeta\zeta')\Lambda' = \Lambda\Phi\Lambda',$$

where Φ contains the covariances among _unique_ components.

The structural model for component interactions is identifiable if elements of Δ and $\underline{D}$ (the δ's) are a computable function of the values in Λ, and if there are a sufficient number of fixed parameters in Λ to allow a unique solution. Identifiable models may be tested by appropriately constraining the elements of Λ and using ACOVS (Jöreskog, 1970) to fit equation (1). The estimates of free parameters in Λ are then used to calculate the required values for the δ's.

Testing Background Correlations among Components

Hypotheses concerning the presence of background correlations among components can be evaluated by comparing a model where the unique components are uncorrelated ($\Phi = I$) with a model in which correlations are allowed ($\Phi \neq I$). In performing these tests, the structure of β and of Λ is, of course, determined by the measurement and structural models. If the model provides an acceptable fit with $\Phi = I$, it may not be necessary to test the alternative model.

In the remainder of this paper, each of the steps I have described will be applied to data obtained from studying the components of reading. First, the measurement tasks developed for each of the three general skill areas will be described. For each skill domain, the procedures for testing and fitting a measurement model will be presented. The validity of the resulting measurement models will be established through comparative model fitting. By testing a series of alternative measurement models which differ from the hypothesized model in particular features, the critical characteristics of a "correct" model are established. Finally, in a subsequent section I will describe and apply the procedures for developing and testing structural theories of component interaction. Structural models will be presented first for the word analysis domain, and second, for the integrative and discourse analysis domains. The status of "general reading ability" as a construct will be evaluated in the light of these structural models.

COMPONENTIAL ANALYSIS OF READING SKILLS

Subjects

Subjects in this study were 48 high-school-age readers chosen to represent a wide range of ability. They were recruited from two schools, an inner-city school and a suburban school. Subjects were selected to represent a wide range of reading ability, as measured by percentile ranks on the Nelson-Denny Reading Test. Each potential subject was administered the entire Nelson-Denny Test: a vocabulary test, a timed reading passage, and a series of comprehension items. Their total score was the sum of the vocabulary and comprehension scores. The final distribution of total scores for four subgroups of 12 subjects was as follows:

Group 1 (11th - 47th percentile),

Group 2 (48th - 77th percentile),

Group 3 (85th - 97th percentile), and

Group 4 (98th - 99th percentile or greater).

Characteristics of the Reading Components Battery

In the course of eight experiments, conducted over the last three years (see Frederiksen, 1977; 1979; 1980), a series of computer-administered tasks has been developed, each of which appears to meet the conditions we have set for component-specific measurement: (a) Each task clearly involves processing associated with a specified component; (b) its design permits the manipulation of task characteristics in ways that will alter difficulty with respect to the involvement of the particular component; and (c) it has received experimental validation in that mean performance has been shown to vary in the predicted manner with changes in task characteristics. The Reading Components Battery is made up of a subset of the tasks and measures developed in the previous set of experiments. The tasks, and measures, are grouped under three general skill areas: Word Analysis, Discourse Analysis, and Context Utilization.

The Measurement Model for Word Analysis Tasks

The experimental tasks used in studying word analysis components are listed in Table 2, along with the measures derived from each task. These measures were chosen for their componential specificity, and the components they represent are also indicated in the table.

Insert Table 2 about here

Anagram identification task. Subjects were presented with a briefly exposed four-letter stimulus array, followed by a masking field. Stimuli were high frequency words (SALT), pseudowords (ETMA), or unpronounceable nonword anagrams (RTNU). $N = 16$ items of each type were presented at each of 5 durations, ranging from 5 to 45 msec. For each exposure, the number of correctly reported letters was measured (the order of report was disregarded). A logit transformation of the number of letters correct N_c, $\log[N_c/(N-N_c)]$, when plotted against exposure duration, yielded a linear function. Fitting straight lines to this plot provided two descriptive parameters: a location parameter and a slope parameter. The measure employed in the present analysis was the slope parameter: the rate of increase in letter information encoded during an anagram display, measured in logits per second. Rates of encoding anagrams were found to differ for the four groups of readers. They were 364, 378, 406, and 443 logits/sec, respectively, for the four reader groups, ordered from least skilled to most skilled. Since the anagrams were random strings of letters, this measure was interpreted as an index of letter encoding efficiency.

Letter matching task. This task was similar to the letter matching task of Posner (Posner & Mitchell, 1967). Subjects were presented 144 pairs of letters which were similar in physical form (e.g., AA, aa), similar in name but not form (e.g., Aa), or dissimilar (ad, AD, Ad). Letters were presented for 50 msec, and subjects responded by pressing a "same" button when the letters were visually or nominally similar (AA, Aa), and a "different" button otherwise. The difference in "same" reaction times (RTs) for nominally and physically similar letter pairs (the "NI-PI" RT) has been interpreted as a measure of time for retrieval of a letter name, since in the visually similar case subjects are thought to be responding on the basis of a rapid matching of visual features (but, see Carroll, Note 1, p. 163). This difference was calculated for each of our subjects. The means for each of the four reading groups, again in order of ability, were 130, 114, 122, and 87 msec.

Bigram identification. The bigram identification task has already been described in the section on the Measurement of Components, above. In the context of attempting to encode and report the letters making up four-letter English words, subjects were presented displays in which only a single pair of adjacent letters (a bigram) was visible; the other letters were masked by simultaneously presenting an overwriting masking character. On these occasions subjects reported only the target bigram. Low-frequency bigrams were found to be more difficult to encode than high-frequency bigrams, as measured by the RT in reporting them. Likewise, bigrams presented in unlikely locations within the array took longer to encode than bigrams presented in high-likelihood positions. These two measures were interpreted as measures of a reader's efficiency in encoding multiletter units. Large RT differences indicate that the "bandwidth" of frequencies/positional likelihoods over which a reader maintains efficient performance is narrow. Small RT differences indicate efficient performance over a wide range of stimulus conditions. Finally, a third measure was calculated: the increase in RT per unit shift in bigram position from left to right. This measure of scanning time is interpreted as potentially representing both components I and II, since high rates can in principle be achieved when individual letters are rapidly encoded and/or when multiletter units are rapidly encoded.

Pseudoword pronunciation task. In this task, subjects were presented 304 pseudowords which were derived from a like number of words by changing one or more vowels. The pseudowords represent 19 orthographic forms (varying in length [4-6 letters], number of syllables [1 or 2], presence of markers, and vowel type [VV vs. V]). There were 16 examples of each form, 2 for each of 8 initial phonemes. Mean onset latencies for pronouncing pseudowords were measured, along with the experimenter's judgment of correctness of response. Three contrasts among orthographic forms were chosen on the basis of their presumed common effect on difficulty of decoding. These were the increases in onset latency brought about by (a) increasing pseudoword length from 4 to 6 letters, (b) increasing the number of syllables from 1 to 2, and (c) replacing a single vowel with a digraph. (In manipulating any one of these variables, items were counterbalanced with respect to the other factors.) The increases in decoding times were typically greatest for the less able readers: for the four groups of readers, length effects were 55, 37, 29, and 13 msec, respectively; syllable effects were 114, 71, 53, and 22 msec; and vowel complexity effects were 44, 65, 49, and 25 msec. Accordingly, each of these measures is regarded as an index of decoding efficiency.

Word recognition task. This task is similar to the pseudoword pronunciation task, except for the substitution of 304 words for pseudowords. The stimuli included 152 high-frequency words (SFI > 50; Carroll, Davies, & Richman, 1971) and a like number of low frequency words (SFI ≤ 50). The 152 words in each group included 8 representatives of each of the 19 orthographic forms employed in the pseudoword pronunciation task, and these 8 representatives were matched on initial phoneme with their pseudoword counterparts. I sought to construct a scale-free index of the degree of orthographic decoding in the context of word recognition. It was shown in prior research (Frederiksen, Note 2; Note 3) that variability in onset latencies for decoding brought about by changes in orthographic form are reliable. This pattern of change in RT for decoding pseudowords can be thought of as a "trace" of the operation of a decoding process. To the extent that similar changes in word recognition latency are found as orthographic form is similarly manipulated, we have evidence for the operation of a decoding process in word recognition. Our measure of depth of decoding in word recognition is, therefore, the correlation (calculated for an individual subject) of mean pseudoword latencies for each of the 19 orthographic forms with those for words which are matched in orthographic form. A high correlation indicates continued operation of the decoding process and, thus, a high depth of orthographic analysis in word recognition. A low or zero correlation indicates low depth of decoding -- that words are recognized on the basis of their visual form, per se. This measure of depth of decoding was calculated separately for high- and low-frequency words. There were differences among the four groups of readers in their reliance on decoding processes in word recognition. Mean correlations for high-frequency words were .42, .41, .35, and .22 for the four reader groups; the corresponding measure for low-frequency words were .38, .37, .45, and .35. Thus, the evidence suggests that, for a vocabulary of high-frequency English words, the better readers are able to reduce their dependence upon decoding processes below the level required for low-frequency words while the poorer readers are not. These correlations, for high- and for low-frequency words, constitute our measures of processing efficiency in word recognition.

Validation of the measurement model. The componential interpretations offered for the 10 measures of word analysis detailed in Table 2 constitute an explicit hypothesis concerning the form of Matrix B in Equation 1, and as such constitute a measurement model. This hypothesis has been schematically represented in Figure 2. Four components are postulated: Component I, Letter Encoding; Component II, Encoding Multiletter Units; Component III, Decoding; and Component IV, Word Recognition. The variables y_1 through y_{10} stand for the similarly numbered measures in Table 2. Performance on a measure y_i is determined by the skill level in one or more of the components, and by a unique or task-specific error factor ε_i. In evaluating the measurement model, a free parameter is entered into Matrix B for each link between a measure and a component shown in Figure 2. Following this procedure, the hypothesized componential structure is seen to correspond to the following hypothesized form for the Matrix B:

MEASURE	COMPONENT I	II	III	IV
1	V	0	0	0
2	V	0	0	0
3	0	V	0	0
4	V	V	0	0
5	0	V	0	0
6	0	0	V	0
7	0	V	V	0
8	0	0	V	0
9	0	0	0	V
10	0	0	0	V

where V denotes a free parameter or variable to be estimated. In testing this measurement model, no restrictions are placed on the correlations among the components (the matrix Φ^* in Equation 2). This hypothesized measurement model was tested, using Jöreskog's ACOVS program (Jöreskog, van Thillo, & Gruvaeus, Note 4). The resulting value of chi-square (with 27 degrees of freedom) is 38.3, and p = .073. Values of the fitted parameters are presented in Figure 2. (The standard errors of these parameters averaged .20).

Insert Figure 2 about here

While the hypothesized measurement model is judged to be satisfactory, I wished to investigate what features of the model are critical and what features less critical in accounting for the correlations among measures. I thus set out to evaluate three alternative measurement models, each of which focused on a specific distinction among the components hypothesized under the model I have presented. These alternative models are described in Table 3, along with a test of each model against the full four-component model of Figure 2. In the first alternative, measures $\underline{y}_1$ through $\underline{y}_5$ are regarded as indices of performance on a single perceptual encoding component; under this model, a single perceptual system responds to single-letter and to multiletter units, and individuals who are efficient with one type of unit are also efficient with the second. As is indicated in Table 3, this model is rejected, with $\chi^2(4) = 10.83$, $\underline{p} = .03$. In the second alternative model, the parsing of an orthographic array into multiletter units and rule-based decoding of those units are regarded as two aspects of a single decoding process. And again, individuals who are most capable in encoding multiletter units will also be the most capable at analyzing those units. This alternative is also rejected, with $\chi^2(4) = 17.89$, $p = .001$. The third alternative model sought to investigate the distinction between efficiency in decoding and in word recognition. In this model, efficient decoding of pseudowords and recognition of words involve the same process: orthographic decoding of words in the same manner as pseudowords or, perhaps, decoding of pseudowords by analogy with similarly spelled words (Glushko, 1980). Again, the alternative model is rejected, with $\chi^2(3) = 9.24$, $p = .03$.

Insert Table 3 about here

Our conclusion is that each of the four components hypothesized must be represented in the measurement model. These results do not imply that the components are independent. To test this possibility, a fourth alternative model was fit, which was similar to the model in Figure 2 save for the additional constraint that the components are uncorrelated (i.e., that $\Phi = \underline{I}$). The test of this hypothesis yielded $\chi^2(6) = 12.62$, with

$p = .05$, and again we are led to reject this alternative. In order to focus on where the most important intercomponent correlations are found I tested a fifth alternative in which the perceptual components I and II are independent, and the perceptual components are correlated with the decoding component III but are independent of the word recognition component (IV). This model is an acceptable alternative to the original model, with $\chi^2(3) = 2.95$, and $p = .83$. A more thorough analysis of component interactions, using the technique of building a structural equation system (alternative six) will be discussed in a later section of this paper. For the moment, I conclude that (a) each of the components represents a distinct source of expertise among readers, and (b) there are clearly demonstrated correlations among components, indicating the need for a theory of component interaction.

The Measurement Model for Discourse Analysis Processes

Measures related to the processing of discourse are all drawn from an experimental study of anaphoric reference (Frederiksen, in press). The purpose of this experiment was to identify text characteristics that influence a reader´s difficulty in resolving problems of, specifically, pronominal reference. In the process, we hoped to be able to draw some inferences about the procedures used by readers in searching for antecedents and selecting referents from prior text when a pronoun is encountered. The experimental task required subjects to read a series of test passages, one sentence at a time. To motivate them to read carefully, subjects were at times probed for the meaning (referent) associated with a pronoun. This was accomplished by presenting an underscore to mark the probed item. Whenever an underscore appeared, the subject's task was to supply (vocally) the correct referent noun or noun phrase from the preceding text. The major focus of the study was not, however, on the accuracy of performance in the probe task (the four reader groups did not differ in their accuracy in supplying referents), but rather on the time spent in processing sentences containing a pronoun or other referential item. More particularly, we were interested in the changes in reading time that occurred as the difficulty of the reference problem was increased through manipulation of the structure of prior text.

The patterns of reading times obtained under a variety of text conditions supported a model having three distinguishable features: (a) When readers encounter a pronoun they retrieve from memory the available antecedents (nouns or noun phrases matching the pronoun in gender and number); (b) they evaluate those antecedents within the semantic or propositional frame of the sentence containing the pronoun, using those semantic constraints that are present to select the correct referent; (c) some readers appear to adopt a strategy of assigning priority in testing to antecedents that have topical status at the time the pronoun is encountered. For example, topical status is higher for noun phrases appearing as the subject of a sentence (particularly the initial sentence of a paragraph), than it is for predicate nouns.

The choice of measures -- contrasting sets of text conditions -- for use in the present study was based upon this processing model. I sought measures that, while being experimentally independent of one another, would represent each of these three components: Automatic assignment of a topicalized antecedent as referent (numbered VII within the final component list), Semantic evaluation/integration of antecedents within a current discourse representation (numbered VIII), and Exhaustive retrieval of antecedents (numbered IX). The measures selected are described in Table 4.

Insert Table 4 about here

The influence of topical status of an antecedent on the problem of reference was studied by presenting two-sentence texts in which the initial sentence contained two antecedent noun phrases (NPs) which both agreed in gender and number with a pronoun presented as the subject of a second, target sentence. Reading times for the target sentence were longer when the correct antecedent was in the predicate of the initial sentence than when it was the subject, i.e., when it was topicalized. This difference (the first measure in Table 4) is therefore interpreted as a measure of readers' sensitivity to topicality in assigning text referents.

In developing our second measure, we were interested in the effect of a prior, consistent use of the pronoun on reading times for a subsequent sentence containing the same pronoun. In particular, we wanted to see if a pronoun, once assigned a referent, would automatically be given the same referent when it was repeated in a subsequent sentence. The initial sentences again contained two antecedents, the first of which was referred to pronominally in the final sentence. The second (intervening) sentence contained the same pronoun, occurring either as subject or within the predicate. The third sentence, as before, began with the pronoun, used to refer to the same antecedent. The results of this experiment showed that pronouns are not automatically assigned their previous referent when they are re-encountered in a text. Reading times depended on the position of the pronoun in the intervening sentence. They were longest when the intervening sentence began with an alternative noun phrase and contained the pronoun in the predicate; this manipulation had the effect of reducing the topical status of the antecedent referred to pronominally, and introduced a new topic -- the subject of Sentence 2. Reading times were shortest when the intervening sentence began with the pronoun, and thus maintained the topical status of the referent. The difference in reading times for these conditions is thus taken as a measure of Component VII. It is also thought to involve Component VIII, due to the need for subjects to efficiently evaluate and reject alternative antecedents when the pronoun is not topicalized in Sentence 2.

When a pronoun (or other referential expression) is encountered, antecedents must be evaluated within the semantic context of the pronoun. One method I have used to measure this process of semantic evaluation has been to compare reading times for sentences containing collocative reference (reference to a previous lexical category, using a different lexical item; Halliday & Hasan, 1976, p. 284) with sentences in which the problem of reference is made as trivial as possible by simply repeating the lexical item. The former condition requires a reader to search his/her discourse model for lexical categories that are associated with the newly encountered lexical item, and to select from among those categories the ones that are semantically acceptable within the semantic context of the current sentence. Reading times for sentences containing collocative references were longer than those for sentences containing lexical repetitions, and I thus use this contrast (Measure 3) as an index of skill in Component VIII.

A second text manipulation was employed to study the semantic evaluation component: We generated sentences that were semantically ambiguous in that either of two antecedents appearing in the initial sentence would be semantically acceptable. Reading times for such semantically ambiguous sentences were substantially longer than were those for unambiguous sentences, reflecting the fact that for ambiguous sentences it is difficult to decide which antecedent should be regarded as the most meaningful. This difference in reading times (Measure 4) is thus taken to be a function of a readers' speed in evaluating antecedents. However, it is also thought to be related to another factor, the readers' exhaustiveness in retrieving all available antecedents (postulated Component IX). The rationale for this interpretation is the following: If a reader retrieves only a single antecedent from the earlier sentence, it will be found to be semantically acceptable within the current sentence context, and no additional time will be expended in searching for alternative referents. It is only when two or more referents are retrieved that the semantic evaluation of antecedents becomes a difficult problem.

Another text comparison was carried out that focused directly on readers' exhaustiveness in retrieving antecedents. I compared texts in which the initial sentence contained two antecedents with alternative texts in which only a single antecedent was present. In both cases, the correct referent for the pronoun in Sentence 2 was the subject (topic) of the initial sentence. Here I was comparing a situation in which there was a semantically irrelevant NP agreeing in gender and number with the target pronoun against a situation in which there was no additional NP agreeing with the pronoun. The results showed clearly that reading times for reading the target sentence were greater when a second potential referent was present in Sentence 1. Readers thus do appear to retrieve multiple antecedents. The fifth measure was therefore interpreted as an index of exhaustiveness of retrieval of antecedents in solving problems of pronominal reference.

The final text comparison (Measure 6) allowed us to test our componential analysis on a text condition in which one component was expected to contribute to high performance while a second component was expected to hinder performance. The texts began with a sentence containing two antecedent NPs and ended with a sentence referring pronominally to the topicalized NP in Sentence 1. In one set of texts, the incorrect antecedent (the one contained originally in the predicate of the first sentence) was used as the subject of a second intervening sentence, while in the control texts a neutral sentence was used instead as the intervening sentence. For readers who are sensitive to topicality of antecedents, the effect of topicalizing an incorrect antecedent between the referent and pronoun will be to increase reading times; at the same time, readers who are efficient in evaluating antecedents will more quickly reject the inappropriate antecedent and discover the correct referent. I thus predict that Measure 6 will be negatively related to Component VII, and positively related to Component VIII.

Validation of the measurement model. The hypothesized componential analvsis of the six measures derived from the anaphoric reference experiment is represented schematically in Figure 3. This measurement model provided an acceptable fit to the matrix of intercorrelations among measures, with $\chi^2(3) = 3.17$, $p = .37$. The three components of this model can be regarded as independent, since a model constraining the component intercorrelations to be zero could not be rejected ($\chi^2[3] = 1.82$, $p = .61$; see Table 5).

Insert Figure 3 about here

Since this three-component model provides what appears to be a good fit, I set out to test a series of alternative measurement models, in order to determine which are the critical features of the present model. The results of these alternative analyses are presented in Table 5. In the first alternative model, the distinction was dropped between Component VII, Sensitivity to Topicality, and Component VIII, Semantic Integration. We were led to reject this alternative ($\chi^2[4] = 10.01$, $p = .04$), and to conclude that these two components must be distinguished in a componential theory for anaphoric reference. In the second alternative model, Retrieval of Multiple Antecedents (Component IX) and Semantic Integration (Component VIII) are functionally linked and therefore form a single component. This model could not be rejected when compared with the original, three-component model ($\chi^2[3] = 1.97$, $p = .58$). Finally, in the third alternative model, a single component was postulated (combining Components VII and IX) which contrasted the automatic assignment of topic as referent (VII) with the exhaustive retrieval of multiple antecedents (IX). This model also could not be rejected when compared with the original three-component model (here $\chi^2[2] = 2.04$, $p = .36$). I am forced to conclude that the evidence available in the intercorrelations among our six measures is insufficient for establishing the separate status of component IX. For present purposes I therefore adopted the second alternative considered above, and accepted the fact that there would be some ambiguity in the resulting measure of (VIII) Semantic Integration, namely, the tendency to retrieve several antecedents that are the subject of such a semantic evaluation.

Insert Table 5 about here

The Measurement Model for Context Utilization (Integrative) Tasks

The integrative skills which have been postulated allow a reader to combine information contained in semantic and syntactic constraints associated with a discourse context with information contained in the orthographic code in a system which efficiently recognizes words and phrases. Two components of these context utilization processes are (a) activation of semantically related items in memory (the generative use of context), and (b) use of contextual information to increase speed of lexical identifications. The first component (numbered Component VI) is intended to contrast readers who are low in generative depth with those who are capable of activating a wide network of nodes in semantic memory, some of which may be strongly related to context and others only moderately so. High skill in this component represents what Guilford has termed a "divergent production" ability (Guilford, 1967). The second component (numbered Component V) is exemplified, at one extreme, by readers who emphasize speed of performance over depth of search when reading in context, and at the other extreme, by readers who emphasize depth of search over processing efficiency.

Word recognition in sentence context. Measures developed for these context utilization components are drawn from two experimental tasks described in Table 6. The first task is an extension of the Pseudoword and Word Decoding Tasks outlined in Table 2. In this task, subjects are asked to pronounce target words that are either tightly or loosely constrained by a prior context sentence. For example, consider the following sentence, in which the final word has been deleted:

> I reminded her gently that this was something that she really should not ___________.

This sentence frame allows the target word to be any of a number of alternatives: _buy_, _do_, _take_, _see_, _read_, _tell_, and so forth. This sentence represents a moderately constraining context. Contrast this with the following sentence:

> Grandmother called the children to the sofa because she had quite a story to ___________.

Here only a few words remain that fit the sentence: _tell_, _relate_, _present_, and the like. This sentence frame represents a highly constraining context. In the present experiment, 304 words were selected representing 2 frequency classes (high and low), 19 orthographic forms, and 8 initial phonemes, as before. For each word, two context sentences were created representing high and moderate degrees of constraint, as illustrated above. The "constraining power" of these context sentences was scaled in a prior experiment (Frederiksen, Note 3): high constraining contexts allowed an average of 7 words (which was the estimated domain size), while moderately constraining contexts allowed an average of 14 words. By comparing subjects' vocalization latencies for words in highly and moderately constraining contexts with those for words and pseudowords presented in isolation, component-specific measures of performance reflecting context utilization were derived. (For a more detailed discussion of the experimental results, see Frederiksen, 1980; Note 3.)

Insert Table 6 about here

The first two measures are the correlations of pseudoword vocalization latencies obtained for each of 19 orthographic forms with those for high-frequency words presented in moderately constraining context (Measure 1), or for low-frequency words presented in highly constraining context. Such correlations, it will be recalled, measure the extent to which orthographic decoding similar to that involved in analyzing pseudowords is operating as subjects process and pronounce English words. In general, the more highly skilled readers (Groups 3 and 4) showed lower involvement of orthographic decoding that did the poorer readers (Groups 1 and 2). Mean correlations for the two former groups were .18 and .10 for words in moderately constraining context, and .16 and .09 for highly constraining contexts. For the two less skilled groups of readers, the means were .29 and .24 for the moderately constraining context, and .31 and .24 for the highly constraining context. The measures we have constructed are hypothesized to represent two components: (IV) General Efficiency in word recognition, and (V) Increase in speed of word recognition with provision of a reliable context. These measures do not involve Component VI, the Generative Capacity in context utilization, since in each case the target is a likely item for that context. The relations of these measures to Component V are negative since a strong emphasis on speed of responding should lead to a lower depth of decoding.

Measures 3 and 4 are the differences in mean response latencies for words presented in context and in isolation. Large values of these measures indicate a large drop in processing time when a predictive context is provided. Small values indicate a small decrease in speed of word recognition when context is supplied. The mean drop in RT when context is presented varied as a function of reading ability. The mean reduction in RT for all words and context conditions was 88 msec for readers in Group 1, 60 msec for Group 2, 49 msec for

Group 3, and 29 msec for Group 4. These results were substantially the same, even when the target words were of low frequency and only a moderately constraining context was employed. Apparently, it is the least skilled readers who are most apt to increase their speed of responding when a predictive context is presented. Measures 3 and 4 are interpreted as representing the degree of emphasis placed by subjects on speed in applying context when identifying a highly predictable target (Component V).

Measurement of effective visual span. The final experiment conducted within the Reading Components Battery was a study of readers' effective visual span, the amount of information they could encode within a fixation, in the presence and absence of a prior paragraph context. Effective visual span is defined as the distance, in character spaces, from the leftmost to the rightmost character encoded from a phrase presented tachistoscopically. Subjects were presented a passage of text (taken from the Degrees of Reading Power Test; State of New York, 1977), but with the final 4 - 7 words of the final sentence missing. After reading the context passage, subjects pressed a response key to receive the final words of the passage, which were presented in a brief (200 msec) exposure. Their task was to report as many words as they saw, in any order. Controls were included to insure that subjects were fixating an indicated spot near the beginning of the test phrase, at the time the test words were presented. (The spot changed subtly during the 200 msec interval preceding the target, and subjects had to successfully discriminate those changes by pressing a second response key.)

There were two major variables in the experiment: (a) presence or absence of the prior context passage and (b) order of presentation of the words of the target phrase (normal or scrambled). Thus, context effects -- the increments in effective visual span occurring when a prior context passage is provided -- could be measured separately for the case where the target words were presented in an unpredictable sequence and where the target phrase was presented intact.

There were clear differences among groups of readers in the context effects shown under these two test-phrase conditions. Less able readers showed substantial benefits of passage context only when the target words were presented in a meaningful sequence.

The average effects of context for readers in Groups 1, 2, and 3 were 1.20, 1.59, and 2.19 letter positions when the test phrase was intact, but were only .32, .84, and .26 letter positions when the test phrase was scrambled. In contrast, readers of high ability showed large context effects regardless of the condition of the test words. For the top group of readers, context effects were 2.57 letter positions when the phrase was not scrambled, and 2.01 letter positions when the target phrase was scrambled. The similarity in performance under these two conditions suggests that, for highly skilled readers, an automatic spreading-activation process is operating which renders semantically related concepts within the lexicon more accessible.

The measures derived from the visual span experiment are four in number. Measures 5 and 6 (in Table 6) are the increases in visual span that occurred when context was added, for the case where the target words were presented in normal order. The two measures correspond to separate groups of texts, those having high and low scaled readability. Measures 5 and 6 are thought to depend primarily on the sixth component I have postulated: Activation of semantically related concepts in memory. However, since the target phrase is presented in normal word order, I hypothesize that Component VIII, Semantic integration within a discourse model may also play a role in determining levels of performance on these measures.

Measures 7 and 8 are also the values of context effects, again measured for high and low readability tests. Here, however, the target words have been scrambled. Under the present interpretation of Component VI as an automatic activation process, performance on these measures will also depend upon the activation of semantically related concepts. However, since in this case target words do not form meaningful sequences, they are processed individually, and speed in recognizing individual items that are contextually constrained will be advantageous. The speed factor is not thought to be of importance when the target is a meaningful phrase, since in that case groups of words are processed together as representatives of concepts. (Additional evidence for this distinction in size of processing units was found: When test phrases were scrambled, there was a strong effect of the number of words within a test phrase on RT. When test phrases were intact, RT was independent of the number of words they happened to contain.)

Validation of the measurement model. The componential interpretation we have offered for each of the context utilization measures provides a basis for the specification of a measurement model, shown in Figure 4. Subjects performance with regard to these 8 measures is hypothesized to be determined by four reading components: Two of these represent the context utilization skills, (V) Speed set in applying a predictive context, and (VI) Extrapolation of discourse context through activation of semantically related items in memory. The other two components represent processes in word analysis and discourse processing drawn from our earlier studies. These are (IV) Efficiency of processing in word recognition, and (VIII) Semantic integration within a discourse representation. For each of these components, two additional measures were selected from prior analysis, to provide unambiguous identification of these components. For Component IV, Measures 9 and 10 were introduced, representing depth of decoding of high- and of low-frequency words presented in isolation. Measures 11 and 12 were drawn from our prior analysis of discourse processes in the Anaphoric Reference Experiment. Measure 11 represents the increase in reading time when a sentence containing anaphora is ambiguous with regard to the selection of a referent. Measure 12 represents the increase in reading time for sentences containing a collocative reference to an earlier noun phrase, compared with sentences in which the reference problem is already "solved" for the reader -- by simply repeating the antecedent noun phrase.

Insert Figure 4 about here

Within Figure 4, hypothesized relations between components and measures are represented by arrows. Efficient word recognition (IV) contributes to low depth of decoding for words of high or low frequency presented either in context (y_1 and y_2) or in isolation (y_9 and y_{10}). Efficiency in semantic integration (VIII) leads to smaller increases in reading time in solving problems of anaphoric reference (y_{11} and y_{12}), and to larger measures of visual span when the target phrase is a meaningful word sequence (y_5 and y_6). Activation of discourse-related items within semantic memory (VI) leads to increases in visual span when prior context is included, regardless of whether the target words are phrases (y_5 and y_6) or scrambled sequences (y_7 and y_8). Finally, Speed set in applying context (V) leads to increases in speed of word recognition when words are predictable from context (y_3 and y_4), to increases in visual span under conditions where words are scrambled (y_3 and y_4), and to lower depth of decoding when context is provided (y_1 and y_2). The measurement model presented here was fit using the ACOVS program, with no restrictions on intercorrelation among components. The resulting value of chi-square with 42 degrees of freedom was 45.8, and $p = .316$. When the component intercorrelations were restricted to be zero, the statistical test yielded $\chi^2(6) = 11.77$, $p = .07$. Therefore, the possibility of component interactions is considered. To explore which components were correlated, I allowed Components IV and VIII and Components V and VI to correlate with one another, and fixed all other intercorrelations at zero. For this model, $\chi^2(4) = 3.21$, with $p = .52$. Parameter estimates for this measurement model are the ones displayed in Figure 4.

While the measurement model hypothesized here is clearly statistically acceptable, I again tested several alternative models in order to discover which features of the hypothesized model are crucial and which are not. Statistics resulting from this procedure are presented in Table 7. In the first alternative model, Components VI and VIII are combined into a single "Semantic Analysis" factor. This resulted in $\chi^2(5) = 9.25$, $\underline{p} = .10$. Given the face validity of the measurement operations employed to mark each of these components, we reject this possible alternative. In the second alternative model, Components V and VI were combined in a single Context Utilization factor. Here, $\chi^2(5) = 24.99$, $\underline{p} = .0001$. The evidence thus strongly suggests that activation of contextually related items in memory is distinct from the use of such constraints in reducing time for analysis of perceptual/orthographic information contained in words. The significant negative correlation between these components (-.43) indicates that readers who show the greatest depth of context-determined activation within semantic memory show the smallest reductions in word recognition time when a constraining context is provided. Availability of a large number of activated units in memory would seem to reduce the opportunity for primarily context-based word recognition, since perceptual and orthographic information must be analyzed in order to select among the numerous alternatives. Conversely, if the mechanism for extrapolating context is a serial predictive system that generates only a few, high-probability candidate items, then the opportunity for increasing speed in word recognition (and circumventing time-consuming decoding operations) will be greater.

Insert Table 7 about here

Summary

For purposes of studying component interactions, twenty variables were selected from those described in Tables 2, 4, and 6. These variables are listed in Table 8. A single measurement model -- the combined measurement models developed for the word analysis, discourse analysis, and context utilization domains -- was constructed. It is represented by the hypothesized pattern of zeroes and nonzero parameters in the Matrix B, which is also given in Table 8. This model was fit using ACOVS, with no restrictions on component (or factor) intercorrelations. This yielded $\chi^2(133) = 185.35$, $p = .002$. The average of standard errors of factor loadings was .16. Note that while the model can be rejected on purely statistical grounds, it contains only 29 nonzero factor loadings in the Matrix B (out of a possible 160), and in all uses only 57 parameters to account for 190 intercorrelations among variables. This model is therefore adopted as the standard measurement model to be used in the study of interactions among reading components.

Insert Table 8 about here

Maximum likelihood estimates of intercorrelations among the eight components are presented in Table 9. These correlations are attributable to two sources of covariation among components: functional interactions among components, and nonfunctional, etiological factors. In the remainder of this paper, I shall examine, first, the functional sources of correlation among components, as expressed in structural equation systems. After fitting such interactive models, it will then be determined whether residual correlations remain among components that require the postulation of other nonfunctional factors such as "general reading ability."

Insert Table 9 about here

ANALYSIS OF COMPONENT INTERACTIONS

Adopting the validated measurement models for each processing domain, I tested hypotheses concerning interactions among components. This was accomplished by building a set of structural equations describing the hypothesized interactions among reading components, demonstrating identifiability of parameters, and testing the structural model by use of the ACOVS procedure (Jöreskog, 1970). A chi-square test then allowed us to compare our structural models against the "null" case where only the measurement model was specified and all components were free to intercorrelate with one another.

Word Analysis Components

The first application of this procedure concerned the Word Analysis domain, where, on the basis of intercorrelations of 10 variables, four components have been identified: Components I, II, III, and IV represent, respectively, the processes of Letter Recognition, Perceiving Multiletter Units, Decoding, and Efficient Word Recognition (low depth of processing in word recognition). In the interactive model, Components I and II both are hypothesized to contribute to efficient, automatic decoding, since the decoding process requires as input orthographic information. Furthermore, availability of encoded multiletter units facilitates more efficient decoding, since the number of units to be processed will then be reduced. However, Components I and II are themselves hypothesized to be independent, since the input data structures they require (visual features) are readily available for all readers. The effect of these perceptual components on word recognition (IV) is thought to be indirect, through their effect on decoding. Efficient decoding (III) contributes to efficient word recognition (IV) by accelerating the availability of phonologically encoded units. Word recognition also has associated with it a unique component representing the ability to encode words directly on the basis of their visual form. Finally, unique components of decoding and word recognition are assumed to be independent.

The structural model that incorporates these hypotheses concerning components' interactions is presented in Figure 5. And in Table 10 I have shown the derivation of the factor matrix Λ relating measured components to unique components and the methods for estimating parameters. Since there are fewer parameters in $\underline{D}$ and Δ than unconstrained elements in Λ, the structural model is overdetermined. An estimate of nonfixed values in Λ was obtained using ACOVS. The equations in (5) were then used to estimate the δ parameters. These were in turn used to recalculate values for λ_{41}, λ_{42}, and λ_{43} using (4) in Table 10. The ACOVS model was then re-fit with fixed values in Λ, to provide a χ^2 value for the fully constrained model. This test yielded $\chi_1^2 = 1.88$, $p = .17$.

Insert Figure 5 and Table 10 about here

In this structural model, the two perceptual components make independent contributions to decoding efficiency, and thus indirectly effect word recognition. Efficient word recognition is not directly related to the perceptual skills, but is strongly related (with r = .66) to efficient decoding. However, component-specific individual differences are the most important determiners of decoding and word recognition efficiency. Note finally that beyond these hypothesized functional interactions among components, there is no evidence of residual correlations among components.

Interactions with Higher-Level Components

In this section, our problem is that of modelling the relations of the low-level reading components to components of discourse processing, and to those involved in utilizing contextual information to guide lexical retrieval. The procedure for fitting and testing a structural model of component interaction, with modification, can be used to investigate the relations of high-level components to low-level word analysis components.

Method of Analysis

Theories of the interaction between high-level components (of context utilization and discourse analysis) and low-level word analysis components can be stated as systems of structural equations. These equations relate measured performance on particular high-level components to *measured* performance on (a) other high-level components and (b) on the four word-analysis components. Since the goal is to estimate the path coefficients (δ_{ij}'s) relating measured components, it is not necessary to simultaneously model the structural relations among the low-level components. A fairly general structural model which illustrates the properties of structural models we will actually be adopting is given in Table 11. In this hypothetical model, word analysis components (numbered 1-4) are assumed to be correlated. (This is due, it has already been seen, to component interactions that are indicated in the figure by dashed lines. The present model, however, does not specify these relations.) In the model, performance on high-level Components 5 and 6 is determined by levels of skill on Components 3 and 4. Performance on high-level Component 5 is determined, as well, by performance on another high-level component, 6. These two types of assumed relations among components are the types of relations we will be considering later in building our interactive models.

Insert Table 11 about here

The structural equation system corresponding to this model is presented in Table 11, along with a derivation of the factor matrix Λ, expressed in terms of the model parameters -- the path coefficients (δ_{ij}'s). Several observations concerning the matrix Λ are helpful. First, consider the factor loadings for Component 6, corresponding to the final row of Λ.

Performance on this component is determined in the model by performance on low-level measured components, and by a unique component. For this type of variable, the values in Λ give the path coefficients directly. The values of λ_{63} and λ_{64} (corresponding to δ_{63} and δ_{64}) are simply regression coefficients obtained in the regression of Component 6 on Components 3 and 4, and $\lambda_{66} = \delta_{66}$ is an estimate of the error (or unique) component of variance (if we assume in the model that the unique component is uncorrelated with other components). The relations of the factor loadings for Component 5 to underlying model parameters is more complex, since this is a case where the high-level variable is related to low-level components (3 and 4) both directly and indirectly -- through the relationship of Component 5 to a second high-level component, 6. Here, the parameters of are related to the parameters of the structural model by expressions such as $\lambda_{53} = \delta_{53} + \delta_{63}\delta_{56}$, which contains two additive terms: δ_{53}, representing the direct path from Component 3 to Component 5, and $\delta_{63}\delta_{56}$, representing the indirect path from Component 3 to Component 5 via Component 6. Likewise, $\lambda_{56} = \delta_{56}\delta_{66}$ represents the path from unique Component 6 to Component 5 via measured Component 6. In developing and testing models for the interaction of high-level components and word analysis components, I shall encounter each of these situations, exemplified by Variables 6 and 5 in the above example. Several of the high-level components will simply be regressed on the set of word analysis components as was Variable 6. And one of the high-level components will be dependent upon a second high-level component as well as on the word-analysis components, as was the case for Variable 5.

Structural Models of Component Interaction

The initial model of component interactions incorporated the following hypotheses:

1. Word analysis components of Decoding efficiency (III) and Word recognition efficiency (IV) are hypothesized to directly influence Context utilization components (V and VI), since early retrieval of lexical categories increases time available for activation of semantically/syntactically constrained items in memory.

2. The Generative component of context utilization (VI) directly (and negatively)

influences the Speed component (V), since speed is inversely proportional to the number of contextually-related alternatives that have been activated.

3. Word analysis components of Perceiving multiletter units (II), Decoding efficiency (III), and Word recognition efficiency (IV) are also hypothesized to influence components of discourse processing (VII and VIII). The discourse analysis processes involved in selecting and evaluating referents in building a propositional representation for a sentence take place concurrently with processes of decoding and word recognition, and therefore must share processing resources with them. High levels of automaticity in word analysis components reduce the resource demands of those processes, and thus improve efficiency of concurrent processes of discourse analysis. (However, the direct relation of Component VIII to II was eliminated in the model, since the correlation between those components was nonsignificant: $\underline{r} = -.19$ with a standard error of .20.)

The structural equations for high-level components V-VIII corresponding to these hypotheses are then:

$$\eta_5 = \delta_{53}\eta_3 + \delta_{54}\eta_4 + \delta_{55}\zeta_5 + \delta_{56}\eta_6,$$
$$\eta_6 = \delta_{63}\eta_3 + \delta_{64}\eta_4 + \delta_{66}\zeta_6,$$
$$\eta_7 = \delta_{72}\eta_2 + \delta_{73}\eta_3 + \delta_{74}\eta_4 + \delta_{77}\zeta_7, \text{ and}$$
$$\eta_8 = \delta_{83}\eta_3 + \delta_{84}\eta_4 + \delta_{88}\zeta_8.$$

The second-order factor matrix Λ for this model has the hypothesized structure indicated at the top of Table 12. The hypothesized structure for Φ is also given in Table 12. Here, the unique components V-VIII are assumed to be independent.

Insert Table 12 about here

To evaluate the fit of this structural model, two more general models were constructed. In the first (Model 2), the four high-level components were regressed on all low-level components. The nonsignificant chi-square of 12.86 (with df = 7) indicates that the restrictions of the original model are supported. To evaluate assumptions concerning the independence of high-level unique factors, a second alternative model was constructed (Model 3). In this model, the high-level components are allowed to freely intercorrelate with one another, instead of introducing the explicit dependency relations between the two context utilization components V and VI. The obtained chi-square of 9.63 (with _df_ = 5) is again not found to be significant, and the assumption of independence of the unique components is supported. Thus, the obtained correlations among high-level measured components can be attributed entirely to their common dependence on levels of automaticity/efficiency of low-level components, and to the specific dependency relation hypothesized for the context utilization components.

Summary of interactions for discourse analysis components. The relationships of discourse processing components to low-level components are illustrated in Figure 6, which contains the estimated path coefficients. Component VIII represents efficiency in integrating semantic information associated with an antecedent lexical item, with the semantic representation being formulated by the reader for the current sentence or phrase. This skill was established, for example, by comparing reading times for sentences containing an ambiguous pronominal reference with those for a sentence containing an unambiguous reference. Semantic integration is not significantly associated with Word recognition (IV), but it is strongly associated with Decoding efficiency (III), with r = .87 and a regression coefficient of .91. Thus, there is a direct effect of automatic decoding on this discourse processing component. This direct influence is interpreted as an example of process interaction due to competition for a limited resource (Perfetti & Lesgold, 1977). Perfetti and Lesgold (1979) have subsequently suggested that the resource limitation is in working memory capacity, and that inefficient decoding requires space in working memory that would otherwise be utilized for discourse processing. Whatever the nature of the resource limitation, it is clear that efficient decoding has an important, direct impact on discourse processing. And one is led to entertain the hypothesis that training for automatic decoding may have an impact on efficiency of discourse processing.

Insert Figure 6 about here

The remaining discourse processing component I have identified, (VII) Preference for a topicalized antecedent as a referent, is reflective of a dependence on the part of the reader on the topical status of antecedents in effecting retrieval from memory. This component was measured, for example, by comparing reading times for sentences containing a pronoun for cases where the referent was topicalized or not topicalized in the first sentence of a paragraph. Component VII is associated with several word analysis components, suggesting again that automaticity of low-level processes contributes to efficiency in processing at the text level, presumably through lessened demands on the processing resource.

Finally, while the investigation of discourse analysis components is still in its infancy, the results we have obtained so far suggest that components in that domain may be independent. Training targeted at one component under those circumstances would not be expected to generalize to other components. This expectation does not hold for word analysis components, where increased automaticity could contribute to efficiency in a variety of discourse-related components.

Simplified model for interactions of context utilization components. Several simplifications in the relationships of context utilization components to low-level components were introduced, and found to be acceptable. These are the Models 4 and 5 in Table 13. The first simplification is based upon the feeling that the basic process of context utilization is the Generative component (VI), and the Speed component represents an optional strategy that some subjects employ: that of trading off speed in responding against the possibility of errors of identification that can occur when the amount of orthographic/phonological evidence developed is being minimized during reading in context. In this model, all correlations between the Speed component (V) and low-level components are regarded as attributable solely to its dependency on the more basic Generative component (VI). The structural equation corresponding to Component 5 thus becomes

$$\eta_5 = \delta_{55} \zeta_5 + \delta_{56} \eta_6 .$$

The other structural equations were, of course, unchanged. Comparison of this model (Model 4) to the original model yielded $\chi^2(2) = .61$, and thus strongly justified the first simplification.

Insert Table 13 about here

A further simplification also proved possible. In the final structural model (Model 5), the direct influence of the Decoding component (III) on Context utilization (VI) was eliminated. This simplification was motivated by the feeling that the generative use of context is an automatic process, one that is not likely to be in competition for processing resources with an inefficient decoding process. Thus, the influence (correlation) of Decoding efficiency with Context utilization should entirely be attributable to its effect on efficiency of word retrieval -- Component IV. Comparison of this model (which included the simplifications of Model 4 as well) with the original model yielded $\chi^2(3) = .94$, again providing strong support for the reasoning behind the simplification.

The final pattern of process interactions for the context utilization components is summarized in Figure 7. Components I - IV are, again, the word recognition components, interrelated as in Figure 2. Component VI, Generating extrapolations from a discourse representation, and V, Speed set in employing highly predictive context, are the two identifiable aspects of context utilization. The generative component, VI, is related directly to Word recognition efficiency (IV), and indirectly to the other word analysis components, through their effects on IV (Word recognition). The path coefficient (-.46) is negative since for the generative component high values (large increases in visual span with the provision of prior context) indicate efficient performance. (For the other components, low values reflect efficient performance.) The interaction of Component VI, Generative use of context, with word recognition efficiency is in theory due to the increased time for activation of semantically associated lexical units when words are more rapidly encoded. Component V, Speed set in utilizing predictive context, is negatively related to the generative component (VI). It represents a strategy that is most applicable when the generative component yields a small (unitary) set of constrained alternatives. The correlations of the strategic component (V) with other components are all attributable to its relation to the more basic generative component. Note, finally, that the greatest factors contributing to context utilization components are the unique components which, in this model, are mutually independent.

Insert Figure 7 about here

RELATIONSHIP OF READING COMPONENTS TO OTHER COGNITIVE FACTORS

Eleven tests representing five cognitive factors were drawn from the ETS Kit of Reference Tests for Cognitive Factors (French, Ekstrom, & Price, 1963). The tests selected are listed in Table 14 for each of the factors. The first three factors represent perceptual skills. Speed of Closure tests require the subject to identify figures or words on the basis of their overall visual form, without benefit of specific features or details. Flexibility of Closure tests require the reader to maintain in memory a specific figure, so as to identify it when it occurs embedded within a larger figural context. Tests of Perceptual Speed measure the rate at which subjects can identify simple figures, or letters, amid an array of distractors.

Insert Table 14 about here

The last two factors are measures of the accessibility of items in lexical memory when memory is searched for items having particular features, of a phonological (orthographic) or semantic nature. Word Fluency tests measure the number of lexical items that can be retrieved in a fixed time that have particular phonological/orthographic characteristics: that begin, or end, with a particular set of letters (e.g., begin with PRO-, SUB-, or end with -AY, -OW). Fluency of Association tests measure the number of lexical items that can be generated within a designated time that bear semantic/associative relationships to a given word or words. In the Controlled Associations test, all words having meanings similar to a given word (e.g., DARK) must be supplied. In the Doubly-Constrained Associations test, words must be found that are simultaneously associated with two presented words (e.g., JEWELRY - BELL; answer: ring). The Simile Interpretation test requires subjects to list as many interpretations for a simile as they can think of, within a timed period.

The factor model for this set of measures is also shown in Table 14. It reproduces the pattern of factor loadings typically posited for this set of variables, with the single exception that Measure 4 (Hidden Patterns), which is a highly speeded test, loads on

Speed of Closure and Perceptual Speed, as well as on Flexibility of Closure. Correlations among the five factors are given in Table 15. Correlations among the perceptual factors are low, while the correlation between the two fluency factors is extremely high (.86). And correlations between the fluency factors and perceptual factors are sizeable.

Insert Table 15 about here

Correlations of reading components with cognitive ability factors were obtained by adapting the ACOVS program for performing an interbattery factor analysis. The results, presented in Table 16, generally supported the interpretation of reading components I have presented. Speed of Closure, a factor reflecting the ability to recognize words on the basis of their overall visual characteristics, correlated with each of the word analysis components except letter recognition efficiency, and most highly with Component IV, Efficiency in word recognition. Flexibility of Closure, a measure of the ability to rapidly recognize familiar visual forms embedded in a larger context, was not correlated with any of the reading components. And

Perceptual Speed, measured by two tests of visual search (for a target letter or picture), was generally correlated with all components, suggesting that this factor is componentially nonspecific. Two additional cognitive abilities were included that are measures of word accessibility, via orthographic/phonological structure (Word Fluency) or by semantic features (Fluency of Association). The two fluency factors are highly correlated (r = .89). There was a general "background" correlation of -.30 to -.40 of these factors with the reading components. Beyond this background correlation, it is interesting that, of these two factors, the factor measuring word accessibility via orthographic/phonological cues was more highly correlated with Decoding efficiency (-.85) and Word recognition efficiency (-.61). And Fluency of Association was more highly correlated with Component VI, Extrapolation of discourse representation (r = .70), a component that shares with the fluency factor a need to access lexical items on subtle semantic grounds. It is interesting that Component VIII, Semantic integration of antecedents, is not tapped by either of the fluency measures. This component, I believe, does not involve divergent production of semantic relations, but rather the specific testing of retrieved antecedents within the semantic frame under construction in working memory.

Insert Table 16 about here

EXAMINATION OF THE READING ABILITY CONSTRUCT

Composite Measures of Reading Ability

It is well known that tests of reading ability, comprehension, vocabulary, and general verbal fluency correlate highly with one another (cf. Davis, 1971). When batteries of such tests are factor analyzed, a general factor of "verbal facility" is typically extracted and interpreted as evidence for an underlying aptitude dimension. The question at issue is how we can reconcile the empirical demonstration of an "ability" dimension that is easily and reliably measured with the theoretical view of reading as a collection of interacting, but largely independent, components of skill.

From the standpoint of componential theory, general reading tests are complex, requiring what is potentially a large number of individual component processes for their successful completion. High levels of tested skill will be found for readers who have achieved high levels of automaticity in a large proportion of those components, and low levels of performance will be found for readers for whom the set of automatic components is more restricted. The model I am advocating here is a compensatory model for determining the overall performance of a system of components as it is represented by scores on a composite reading task. Within a compensatory model, high levels of skill in one component can compensate for low levels in another. Performance on the composite task is thus taken to be a linear function of the skill levels on individual components.

It is easy to show that a high correlation between two composite measures of reading is to be expected within the framework of such a compensatory model, even in the case where the underlying reading components are mutually independent. Let $\underline{t} = \sum_i \underline{w}_i \underline{y}_i$ represent performance on one composite reading task, and let $\underline{s} = \sum_i \underline{v}_i \underline{y}_i$ represent performance on a second reading task. Each composite task is a linear combination of performance levels on a set of components, represented by $\underline{y}$. If we further assume that the variances of the components are 1 and scale the weights ($\underline{w}_i$ and $\underline{v}_i$) so that their sum of squares is 1, then the correlation between the composites $\underline{t}$ and $\underline{s}$ is given by

$$(8)\quad \rho(\underline{t},\underline{s}) = \frac{\sum_{i}\underline{w}_i\underline{v}_i\rho(\underline{y}_i,\underline{y}_i{}') + \sum\sum_{i\neq j}\underline{w}_i\underline{v}_j\rho(\underline{y}_i,\underline{y}_j)}{[1+\sum\sum\underline{w}_i\underline{w}_j\rho(\underline{y}_i,\underline{y}_j)]^{\frac{1}{2}}[1+\sum\sum_{i\neq j}\underline{v}_i\underline{v}_j\rho(\underline{y}_i,\underline{y}_j)]^{\frac{1}{2}}}$$

where $\rho(\underline{y}_i, \underline{y}_i{}')$ is the reliability of the $\underline{i}$th component, and $\rho(\underline{y}_i, \underline{y}_j)$ is the correlation between the two discrete components $\underline{i}$ and $\underline{j}$ (see Lord & Novick, 1968, pp. 97-98). If we now introduce the further condition that the components are independent (that $\rho[\underline{y}_i, \underline{y}_j] = 0$), Equation 8 can be simplified to yield

$$(9)\quad \rho(\underline{t},\underline{s}) = \sum_{i}\underline{w}_i\underline{v}_i\rho(\underline{y}_i,\underline{y}_i{}').$$

Finally, if actual component automaticities/performance levels are substituted for measures of those quantities, the reliabilities will be 1 and the correlation between the two composites will be simply the correlation between the weightings of the components for the two composite tasks. Thus, two composite measures having similar weighting on a set of component processes will be highly correlated, even if the components operate independently. If the components are not independent (i.e., they interact), the correlation will be less dependent on the similarity of weights for the two composite measures of reading. High correlations among reading tests are therefore to be expected, as long as the tests represent componentially complex composites of individual components and the weightings of components are similar. It follows that the fact that batteries of reading tests generally yield a large general factor has no bearing whatever on the componential complexity of the reading process represented in the tests. Such a finding only suggests that the composite tests that make up the battery are making similar demands on a set of underlying reading components. It is only when the individual measures within a test battery are constructed so as to be componentially specific that the high, positive correlation among measures will be eliminated and the pattern of component interactions will become apparent.

Componential Analysis of Reading Tests

Given a set of measures of reading components resulting from the application of the measurement model displayed in Table 8, it is possible to study the relation of several composite measures of reading ability to underlying reading components. The correlations of the eight reading components and four criterion measures of reading ability were estimated using the ACOVS program and are given in Table 17. The four criterion measures are reading time for context paragraphs in the Visual Span Experiment, the number of lines of text read in the Nelson-Denny timed reading passage, and the Nelson-Denny vocabulary and comprehension subtest scores.

Insert Table 17 about here

There are consistent relationships between word analysis components and the four criteria, including the comprehension subtest. Decoding efficiency and Word recognition efficiency both correlate highly with vocabulary and comprehension measures, and with the computer-based measure of reading speed. Component II, Perceiving multiletter units, is also moderately correlated with three of the criterion measures. The letter encoding component appears to be of lesser importance for the tests that are specifically reading tasks, but does correlate -.31 with vocabulary. (This value is in close agreement with the one obtained by Hunt, Lunneberg, and Lewis, 1975.) The finding of high correlations of word analysis components and measures of comprehension is consistent with results of Perfetti and Lesgold (1977; see also Perfetti & Roth, 1980). Together, these findings provide additional support for the hypothesis advanced in our interactive model, that automaticity of word analysis skills is essential in order to free processing resources for the purposes of discourse analysis.

While the majority of word analysis components are strongly correlated with criterion measures of reading ability, measures of high-level components are less generally predictive of reading ability -- at least as it is measured by conventional tests of reading speed and comprehension. Of the context utilization components, the most prominent is Component VI, the generative process of extrapolating a discourse representation in the activation of semantically constrained items in memory. This component correlates .59 with comprehension, and is also highly correlated with the other reading measures. The correlation of .47 of this component with the vocabulary test suggests that general knowledge of word meanings may be one prerequisite for developing skill in the generative use of context.

Finally, and surprisingly, neither of the discourse analysis components is strongly correlated with conventional reading test measures of speed, vocabulary, or comprehension. Component VII, Influence of topicality in assigning reference relations, correlates -.34 with comprehension, indicating that good comprehenders are less influenced by the topical status of a referent in analyzing anaphoric relations in a text. Component VIII, Semantic integration, appears to be poorly "tapped" by the conventional reading test measures; it correlates highly with only the computer-timed measure of reading speed (r = .41). This finding serves to remind us that there are discourse processing skills that would appear to have broad applicability in processing text, but that are only poorly represented in conventional tests of reading comprehension.

Status of the Reading Ability Construct in Componential Theory

Apart from the identification of "reading ability" with performance on a composite test of reading performance, can a role be found for a reading ability construct within componential theory? One possibility is that an explicit, theoretical definition of reading ability as a processing component can be developed. For example, reading ability might be equated with a single component such as "constructing a propositional representation of a text." The problem with this approach is that, in our attempt to be theoretically explicit in defining the component, we are likely to discover that the proposed process is itself multicomponent, and each of the resulting subcomponents is likely to be too specific to qualify as a general reading ability. It is probably the case that any reasonably general processing system is resolvable into a set of more particularized components, together with their interactions. Nevertheless, it is possible for components to be grouped in more general systems. For example, even though the decoding component we have studied includes subprocesses for syllabication and for translating digraph vowels, measures of those subcomponents can be regarded as indicators of efficiency of a more general decoding system. The empirical check on the validity of a component as an integrated system of subprocesses is in the convergent and discriminant validity exhibited by the collection of subprocess measures, as they are evaluated in the fitting of a measurement model. Thus, it is in theory possible to identify a system of components that are process-linked and that together perform a type of text analysis that could be considered a primary ability in reading. However, the components of discourse analysis we have analyzed to date do not appear to be closely related aspects of a single system for text analysis.

A second possible locus for general reading ability within a componential model lies in the concept of resource or capacity limitation, used to explain interactions between low- and high-level components of reading. Low reading ability might be thought of as a result of restricted processing resources (Kahneman, 1973; Norman & Bobrow, 1975), or perhaps, restrictions in working memory capacity (Perfetti & Lesgold, 1977). Such an explanatory concept has not been limited to reading, however. For instance, limitations in attentional resources have been proposed to explain age-related deficits in memory (Craik & Simon, 1980; Kinsbourne, 1980). Furthermore, factor analytic studies of resource-sharing measures (contrasts in performance for a task performed alone or concurrently with a second task) have provided no evidence as yet for a general factor reflecting a common attentional resource component (Sverko, Note 5). The only factors that could be extracted in the Sverko study were clearly task-specific. Other students of the resource-sharing "ability" (Hawkins, Church, & DeLemos, Note 6) have reached similar conclusions. Resource capacity limitations, if they exist as stable aspects of individuals, are multifaceted and task-specific. Thus, it is difficult to see how reading ability could be conceptualized as a general limitation in processing resources. Deficits in reading-related processing resources might, however, contribute to poor performance on composite reading tasks.

We are left with a third possible interpretation of reading ability within componential theory, one that is based on the background environmental and biological factors that condition levels of performance on components. According to this view, etiological factors such as these enable some individuals to acquire high levels of skill in numerous components, while others remain incapable of developing such general expertise across the skill domains of reading. This essentially empirical definition of reading ability is similar to the identification of verbal ability as the general or "g" factor underlying a series of verbal tests, or the equating of a first principle factor with "general intelligence." There is a difference, however: Here we are dealing with components, not with tests that are composites of components. Given a set of theoretically-derived measures of components that have met the two standards of validity I have proposed, empirical evidence for general ability will be found in the presence of background correlations among components, correlations that remain after removing any covariation that is attributable to theoretically proscribed interactions among components. The results so far provide no evidence of such background correlations, and thus offer no support for an underlying general factor of reading ability.

DISCUSSION

In this paper, I have attempted to outline the form of a procedure-based componential theory of reading, and to develop multiple standards by which the validity of such a theory can be judged.

The first level of validation concerned the ability to predict mean performance on a criterion measurement task for a set of particular task conditions. These predictions are based on an information-processing theory offered for the criterion task. In the experiments I have reported, separate tasks are generally employed to measure each of the specific reading components under investigation, and the selection of component-specific measures is based upon the particular processing model developed and validated for each task. An alternative approach has been used by Sternberg (1977) in his studies of reasoning abilities: Rather than working with a set of experimental tasks, a single criterion task is chosen which, while representing a componentially-complex (composite) performance, is susceptible to a variety of parametric variations in task conditions. A multicomponent theory is developed for predicting performance on the criterion task, and a "componential analysis" is advanced stating the theoretical degree of involvement of each component for each of the task conditions. A regression equation is then fit in which mean performance on the criterion task is predicted from the theoretically specified component weights for each of the task conditions. These regression equations can be fit to data for groups of subjects, or for individuals. The goodness-of-fit of the componential model is indexed by the multiple correlation obtained in predicting composite performance from the theoretically specified component involvements.

And the regression weights are interpreted as measures of the efficiencies of the individual components. These weights are in fact contrasts among the task conditions, and as such are formally similar to the component-specific measures we have been developing. Carroll (1980) has shown how these beta weights may serve as variables in further analyses of covariances among components, through the use of factor analysis.

Level One validation can be thought of as equivalent to building and testing a theory of item or task difficulty. Rather than simply scaling item difficulties by applying a standard statistical theory of task performance (e.g., a latent trait theory), an information-processing theory of task performance is fit to the performance records for each individual, and parameters of the theoretical model are taken as the "test" measures. This approach has been explicitly adopted by Brown and Burton (1978), who have shown how, by applying a theory of performance on arithmetic problems, patterns of errors can be used to identify specific conceptual "bugs" within the individual´s information-processing system. The hope in adopting such an approach is that a cognitively rich theory of task performance will yield measures of particular features of an individual's processing system. These measures will in theory reveal the status of particular processing components, rather than merely reflect the operation of the overall system as it is performing a composite task.

The second level of validation was concerned with the differences in levels of component-specific performance evidenced by individual subjects, over a set of measures that have been found to conform to the Level One standards of validity. We have attempted to show how the componential theory developed for predicting the effects of task manipulations in Level One validation implies as well a highly specific measurement model, which relates performance on one measure to that on other measures of similar or dissimilar components. This measurement model can be statistically evaluated using techniques of confirmatory maximum-likelihood factor analysis. I believe that the logical correspondence between theoretically-derived hypotheses underlying Level One and Level Two validation is a tight one. If two measures share a processing component according to the model developed in Level One validation, then they must be resolvable as functions of the same underlying component in fitting a measurement model, and their correlations with other measures must be proportional to their weights (loadings) on the underlying common component. Any violation of these relationships suggests that there is an unanticipated functional independence between measures, and that further theoretical specification will be needed to account for the discrepancy. It is only when a measure is found to be totally unique -- to be uncorrelated with all other measures -- that there is ambiguity in the theoretical interpretation of the outcome. (Here the measure may represent some theoretically unspecified component, or it may simply be unreliable.) Finally, it should be emphasized that the testing of measurement models underlying the covariances among component-specific measures is not factor analysis in the usual sense, since here the factor structure is specified in advance of the analysis.

A componential theory not only specifies the processing components underlying each of the experimental measures introduced; it must also provide for an analysis of component interactions. The procedural view of components provides a means for predicting when components are linked, and when they are not. According to this view, components are invoked whenever particular situations -- or data structures -- occur, and they operate in specified ways upon those data structures. Components are thus linked through their operation on a common internal data base, and through the joint demands they place upon shared processing resources. The specification of a theory of component interaction therefore requires specific knowledge of the attentional demands and of the levels of automaticity of the components. Particular theories of component interaction can be stated as systems of structural equations, and the parameters of those equations (the path coefficients) can be estimated (at least for some models) by the use of maximum likelihood techniques for the analysis of covariance structures. The alternative to this structural modelling approach is the use of training studies. The results of componentially specific training should transfer to other componentially specific measures, as specified in the theory of component interaction.

Finally, the componential theory of reading has provided a basis within which I could reexamine the concept of "general ability" in reading. The existence of a large general factor in the analysis of composite reading tests was shown to be an expected outcome, given a compensatory model relating processing components to composite test performance. I believe there is little hope for uncovering component skills in reading by the analysis of correlations among such composite tests. What is needed is a set of theoretically based, componentially specific measures that have met the standards of validity that have been proposed. If a set of such measures is available which covers the broad range of component skills of reading, it should be possible to test for a general, background correlation among reading skills attributable to general ability. Evidence for such a correlation has so far been lacking. However, a stronger and more definitive statement concerning an underlying "verbal ability" must await further evidence, and more particularly, the development of a more articulated componential theory for discourse analysis. Nevertheless, I feel that the approach outlined here might fruitfully be applied in other areas of complex cognitive performance, and serve as a means of resolving the ongoing interminable debate concerning the existence and nature of general intelligence.

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Table 1

Types of Component Interactions

- I. Functionally Determined Interaction
  - A. Data-linked Components
    - 1. Correlated Input Data
    - 2. Cascaded Processes
    - 3. Dependent Processes
    - 4. Mutually Facilitory Processes
  - B. Process-linked Components
    - 1. Shared subprocesses
    - 2. Shared control processes
  - C. Resource-linked Components
    - 1. Due to general processing capacity
    - 2. Shared memory access/retrieval channels
    - 3. Limited capacity working memory
- II. Nonfunctional Sources of Process Intercorrelation
  - A. Etiologically linked components
    - 1. Reflecting a learning hierarchy
    - 2. Reflecting effectiveness of learning environments
  - B. Reflecting general, biologically determined ability

Table 2

Reading Components Battery:
Word Analysis Tasks and Measures

Experimental Task	Derived Measures	Components[a]
A. ANAGRAM IDENTIFICATION: Subjects report letters seen within a briefly presented, masked display containing 4-letter anagrams.	1. Rate of letter encoding, inferred from increase in logit (Prob. Correct) per unit increase in exposure duration.	I
B. POSNER LETTER MATCHING: Subjects respond same or different on basis of similarity of letter names.	2. RT (Aa) - RT (AA)	I
C. BIGRAM ENCODING: Subjects report letters seen within a briefly presented, masked display containing 4-letter words; on critical trials, all letters except a single bigram are simultaneously masked.	3. Increase in RT for low frequency compared with high frequency bigrams.	II
	4. Scanning Rate: Increase in RT for each shift (left to right) in bigram position.	I, II
	5. Increase in RT for bigrams having low positional likelihood.	II
D. PSEUDOWORD PRONUNCIATION: Subjects pronounce pseudowords which vary in orthographic structure (in length, syllables, and vowel type).	Increase in vocalization onset latency for:	
	6. Digraph vowels compared with simple vowels.	III
	7. Increase in array length from 4 to 6 letters.	II, III
	8. Two syllables compared with one syllable.	III
E. WORD RECOGNITION: Subjects pronounce words which vary in frequency and orthographic structure.	Correlation of pseudoword onset latencies obtained for each of 19 orthographic forms with those for:	
	9. High-frequency words presented in isolation.	IV
	10. Low-frequency words presented in isolation.	IV

[a] I. Letter encoding efficiency, II. Perceiving multiletter units, III. Decoding or phonological translation, IV. Efficiency in word recognition.

Table 3

Comparison Among ACOVS Models for Word Analysis Components

Alternative Model[a]	Number Components	Number of Parameters	Chi Square	df	Probability
1. A single Perceptual Encoding Component; Combine Components I and II	3	14	10.83	4	.03
2. A single Orthographic Analysis Component; Combine Components II and III	3	14	17.89	4	.001
3. No distinction drawn between Decoding Efficiency and Decoding Depth; Components III and IV combined	3	15	9.24	3	.03
4. Test of independence of original four components	4	12	12.62	6	.05
5. Test of independence of Components I and II, I and IV, and II and IV	4	15	2.95	3	.83
6. Test of structural model, with links between Components I and III, II and III, and III and IV	4	17	1.88	1	.17

[a] Alternatives are each tested against the full 4-component model, containing 18 parameters.

Table 4

Reading Components Battery:
Discourse Analysis Tasks and Measures

Experimental Task	Derived Measures	Components[a]
ANAPHORIC REFERENCE EXPERIMENT: Subjects read texts containing pronouns, and supply referents for pronouns whenever an underscore appears beneath them.	Differences in reading times for sentences containing anaphora under contrasting text conditions:	
	1. The correct antecedent is not topicalized/topicalized in the initial sentence.	VII
	2. The pronoun appears in the predicate / as the subject of a sentence intervening between referent and target.	VII, VIII
	3. The correct antecedent is referred to collocatively/by lexical repetition within the timed sentence.	VIII
	4. The correct antecedent is semantically ambiguous/unambiguous within the target sentence.	VIII, IX
	5. Two/only one antecedent nouns phrase(s) agreeing with the pronoun are (is) present in the initial sentence.	IX
	6. An incorrect antecedent noun phrase appearing in sentence one is/is not repeated as the topic of an intervening sentence which occurs prior to the target.	-VII, VIII

[a] VII. Assignment of topicalized antecedent as referent, VIII. Semantic integration/evaluation of antecedents with discourse representation, IX. Exhaustive retrieval of antecedents.

Table 5

Comparisons Among ACOVS Models for Measures of Discourse Analysis

	Alternate Model[a]	Number of Components	Number of Parameters	Chi Square	df	Probability
1.	No distinction between sensitivity to topicality and semantic integration; Combine Factors VII and VIII	2	8	10.01	4	.04
2.	No distinction between Semantic Integration and Retrieval of Multiple Antecedents; Combine VIII and IX	2	9	1.97	3	.58
3.	A single factor contrasting Rapid Assignment of Topic vs. Retrieval of Multiple Antecedents; Combine VII and IX	2	10	2.04	2	.36
4.	Test of independence of original 3 factors	3	9	1.82	3	.61

[a] Alternatives are tested against the full three-component model, containing 12 parameters.

Table 6

Reading Components Battery:
Context Utilization Tasks and Measures

Experimental Task	Derived Measures	Components[a]
WORD RECOGNITION IN SENTENCE CONTEXT: Subjects pronounce words which vary in orthographic form, presented in a high or low constraining context.	Correlation of pseudoword onset latencies obtained for each of 19 orthographic forms with those for:	
	1. High-frequency words presented in moderately constraining context.	IV, (-)V
	2. Low-frequency words presented in highly constraining context.	IV, (-)V
	Drop in mean onset latency when words are presented in context rather than in isolation for:	
	3. High-frequency words presented in a moderately constraining context.	V
	4. Low-frequency words presented in a highly constraining context.	V
READING PHRASES IN PARAGRAPH CONTEXT: Subjects report all words seen within a display containing a phrase which completes the context paragraph.	Increase in visual span when context was added for:	
	5. Easy (highly readable) texts	VI, VIII
	6. Difficult (less readable) texts	VI, VIII
WORD RECOGNITION IN PARAGRAPH CONTEXT: Subjects report all words seen within a display containing randomly sequenced words derived from a phrase which would complete the context paragraph.	Increase in visual span when context was added for:	
	7. Easy (highly readable) texts	V, VI
	8. Difficult (less readable) texts	V, VI

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[a] IV. Efficiency in word recognition, V. Speech set in applying context to identify a highly predictable target, VI. Extrapolating a representation of discourse context: Activation of semantically related items in memory, VIII. Semantic integration of antecedents within a currently formulated discourse representation.

Table 7

Comparisons Among ACOVS Models for Measures of Context Utilization

	Alternative Model[a]	Number of Components	Number of Parameters	Chi Square	*df*	Probability
1.	Single Semantic Analysis Factor; Combine Factors VI and VIII	3	19	9.25	5	.10
2.	Single Context Utilization Factor; Combine Factors V and VI	3	19	24.99	5	.0001
3.	Test independence of original four components	4	18	11.77	6	.07
4.	Test independence of Factors IV and V, IV and VI, V and VIII, and VI and VIII	4	20	3.21	4	.52

[a] Alternatives are tested against the full four-component model containing 24 parameters.

Table 8

The Complete ACOVS Model Used in Validity Studies[a]

Measure (Effect)			Component							
			I	II	III	IV	V	VI	VII	VIII
1.	[b]ANAG:	RATE OF LETTER ENCODING	.26	0	0	0	0	0	0	0
2.	LTM:	RT(Aa)-RT(AA)	1.00	0	0	0	0	0	0	0
3.	BG:	BIGRAM FREQUENCY	0	1.00	0	0	0	0	0	0
4.	BG:	POSITION	.19	.58	0	0	0	0	0	0
5.	BG:	POSITIONAL LIKELIHOOD	0	.39	0	0	0	0	0	0
6.	PSEU:	VOWEL TYPE	0	0	.41	0	0	0	0	0
7.	PSEU:	LENGTH	0	.30	.43	0	0	0	0	0
8.	PSEU:	SYLLABLES	0	0	.77	0	0	0	0	0
9.	CORR:	HFW/NC w/PSEU.	0	0	0	.56	0	0	0	0
10.	CORR:	LFW/HCC w/PSEU.	0	0	0	.91	-.30	0	0	0
11.	CONTEXT:	NC-LCC (HFWs)	0	0	0	0	.91	0	0	0
12.	CONTEXT:	NC-HCC (LFWs)	0	0	0	0	1.00	0	0	0
13.	SPAN:	C-NC (PHRASES, EASY)	0	0	0	0	0	.58	0	.42
14.	SPAN:	C-NC (PHRASES, DIFF.)	0	0	0	0	0	.52	0	.28
15.	SPAN:	C-NC (WORDS, EASY)	0	0	0	0	.58	.72	0	0
16.	SPAN:	C-NC (WORDS, DIFF.)	0	0	0	0	.58	.62	0	0
17.	ANAPHOR:	REFERENT NOT TOPIC/TOPIC	0	0	0	0	0	0	1.00	0
18.	ANAPHOR:	PRED./SUBJECT OF INTERV. SEN.	0	0	0	0	0	0	.29	.26
19.	ANAPHOR:	AMB./UNAMB. REFERENCE	0	0	0	0	0	0	0	.61
20.	ANAPHOR:	FOREGRND. NP2/NEUT. INTERV.SEN.	0	0	0	0	0	0	-.33	.46

[a] The average of standard errors is .16.

[b] Variable was reflected in the analysis.

Table 9

Intercorrelations Among Components in Complete ACOVS Model[a]

Component	I	II	III	IV	V	VI	VII	VIII
I. Letter Recognition	1.00							
II. Perceiving Multiletter Units	.12±.15	1.00						
III. Decoding	.49±.21	.35±.17	1.00					
IV. Word Recognition	.25±.18	.10±.16	.66±.16	1.00				
V. Speed Set in Context Utilization	-.09±.15	.10±.14	.34±.16	.32±.24	1.00			
VI. Extrapolating Context	.20±.18	-.15±.17	-.42±.21	-.44±.19	-.51±.18	1.00		
VII. Topicality Set for Locating Referents	.19±.15	.49±.14	.49±.17	.49±.15	.16±.14	.07±.18	1.00	
VIII. Semantic Integration	.22±.20	-.19±.20	.87±.18	.48±.20	.08±.21	.16±.26	.18±.21	1.00

[a] Standard errors are indicated following each correlation.

Table 10

Analysis of Interactions Among Word Analysis Components

Structural Equations

$$
\begin{aligned}
\eta_1 &= \zeta_1 \\
\eta_2 &= \zeta_2 \\
\eta_3 &= \delta_{31}\eta_1 + \delta_{32}\eta_2 + \delta_{33}\zeta_3 \\
\eta_4 &= \delta_{43}\eta_3 + \delta_{44}\zeta_4
\end{aligned}
\qquad (1)
$$

Unique Components as Functions of Measured Components

$$
\begin{aligned}
\zeta_1 &= \eta_1 \\
\zeta_2 &= \eta_2 \\
\delta_{33}\zeta_3 &= -\delta_{31}\eta_1 - \delta_{32}\eta_2 + \eta_3 \\
\delta_{44}\zeta_4 &= - \delta_{43}\eta_3 + \eta_4
\end{aligned}
\qquad (2)
$$

or, in matrix form:

$$
\begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & \delta_{33} & 0 \\ 0 & 0 & 0 & \delta_{44} \end{bmatrix}
\begin{bmatrix} \zeta_1 \\ \zeta_2 \\ \zeta_3 \\ \zeta_4 \end{bmatrix}
=
\begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ -\delta_{31} & -\delta_{32} & 1 & 0 \\ 0 & 0 & -\delta_{43} & 1 \end{bmatrix}
\begin{bmatrix} \eta_1 \\ \eta_2 \\ \eta_3 \\ \eta_4 \end{bmatrix}
\qquad (3)
$$

$$D \qquad \zeta \qquad = \qquad \Delta \qquad \eta$$

Factor Matrix $\Lambda = \Delta^{-1}D$

$$
\begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ \delta_{31} & \delta_{32} & \delta_{33} & 0 \\ (\delta_{43}\delta_{31}) & (\delta_{43}\delta_{32}) & (\delta_{43}\delta_{33}) & \delta_{44} \end{bmatrix}
\qquad (4)
$$

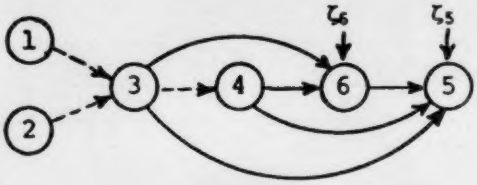
Identifiability of Parameters

$$
\begin{aligned}
&\hat{\delta}_{43} = \text{Average of } \hat{\lambda}_{41}/\hat{\lambda}_{31},\ \hat{\lambda}_{42}/\hat{\lambda}_{32}, \text{ and } \hat{\lambda}_{43}/\hat{\lambda}_{33}. \\
&\hat{\delta}_{31} = \hat{\lambda}_{31} \qquad \hat{\delta}_{32} = \hat{\lambda}_{32} \qquad \hat{\delta}_{33} = \hat{\lambda}_{33}.
\end{aligned}
\qquad (5)
$$

Table 11

Analysis of Interactions Involving Higher-Order Components

Structural Equations[a]



$$\eta_1 = \zeta_1$$

$$\eta_2 = \zeta_2$$

$$\eta_3 = \zeta_3$$

$$\eta_4 = \zeta_4$$

$$\eta_5 = \delta_{53}\eta_3 + \delta_{54}\eta_4 + \delta_{55}\zeta_5 + \delta_{56}\eta_6$$

$$\eta_6 = \delta_{63}\eta_3 + \delta_{64}\eta_4 + \delta_{66}\zeta_6$$

Unique Components as Functions of Measured Components

$$\zeta_1 = \eta_1$$

$$\zeta_2 = \eta_2$$

$$\zeta_3 = \eta_3$$

$$\zeta_4 = \eta_4$$

$$\zeta_5 = -\delta_{53}\eta_3 - \delta_{54}\eta_4 + \eta_5 - \delta_{56}\eta_6$$

$$\zeta_6 = -\delta_{63}\eta_3 - \delta_{64}\eta_4 + \eta_6$$

Factor Matrix $\Lambda = \Delta^{-1}D$

$$\begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & (\delta_{53}+\delta_{63}\delta_{56}) & (\delta_{54}+\delta_{64}\delta_{56}) & \delta_{55} & (\delta_{56}\delta_{66}) \\ 0 & 0 & \delta_{63} & \delta_{64} & 0 & \delta_{66} \end{bmatrix}$$

Identifiability of Parameters

$$\hat{\delta}_{56} = \hat{\lambda}_{56}/\hat{\lambda}_{66},$$

$$\hat{\delta}_{53} = \hat{\lambda}_{53}-\hat{\delta}_{63}\cdot\hat{\delta}_{56},$$

$$\hat{\delta}_{54} = \hat{\lambda}_{54}-\hat{\delta}_{64}\cdot\hat{\delta}_{56},$$

$$\hat{\delta}_{55} = \hat{\lambda}_{55},\ \hat{\delta}_{63} = \hat{\lambda}_{63},\ \hat{\delta}_{64} = \hat{\lambda}_{64},\ \hat{\delta}_{66} = \hat{\lambda}_{66}.$$

---

[a] Components 1-4 are allowed to be freely intercorrelated; the correlation between Components 5 and 6 may or may not be constrained, depending upon the model. Intercorrelations between Components 1-4 and high-level Components 5 and 6 are assumed to be zero.

Table 12

ACOVS Models for Component Interactions with and without Assumptions of Component Independence

Interactive Model[a]	Fixed and Variable Parameters Resulting from the Structural Model (Λ)	Intercorrelations among Components (Φ)	Comparisons among Models		
			χ^2	df	p
1. Restricted model for interaction of higher-order components and word analysis components, assuming component independence.	$\left[\begin{array}{c\|c} I & 0 \\ \hline 00vv & vv00 \\ 00vv & 0v00 \\ 0vvv & 00v0 \\ 00vv & 000v \end{array}\right]$	$\left[\begin{array}{c\|c} \Phi_{11} & 0 \\ \hline 0 & I \end{array}\right]$	--	--	--
2. Unconstrained regression of higher-order components on word analysis components, assuming component independence.	$\left[\begin{array}{c\|c} I & 0 \\ \hline vvvv & vv00 \\ vvvv & 0v00 \\ vvvv & 00v0 \\ vvvv & 000v \end{array}\right]$	$\left[\begin{array}{c\|c} \Phi_{11} & 0 \\ \hline 0 & I \end{array}\right]$	12.86	7	.08[b]
3. Restricted model for interaction of higher-order components and word analysis components, allowing correlation among components.	$\left[\begin{array}{c\|c} I & 0 \\ \hline \begin{array}{c} 00vv \\ 00vv \\ 0vvv \\ 00vv \end{array} & \begin{array}{cccc} v & & & 0 \\ & v & & \\ & & v & \\ 0 & & & v \end{array} \end{array}\right]$	$\left[\begin{array}{c\|c} \Phi_{11} & 0 \\ \hline 0 & \Phi_{22} \end{array}\right]$	9.63	5	.09[b]

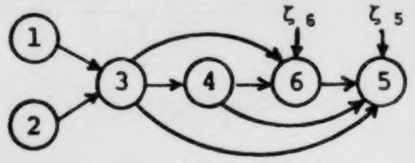
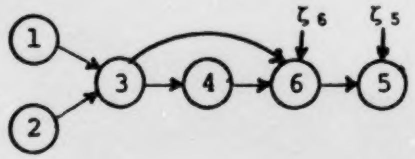
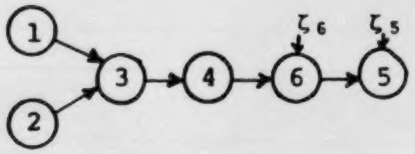
---

[a] The general model is $\Sigma = \beta\Lambda\Phi\Lambda'\beta' + \Theta^2$, where β contains the measurement model, Λ and Φ depend upon the particular structural model, and Θ^2 contains error variances. The rows and columns of Matrices Λ and Φ correspond to the 8 components; Submatrix Φ_{11} contains intercorrelations among word analysis components; Φ_{22} contains intercorrelations among the higher-order components; and I represents the 4x4 identity matrix. Free parameters, or variables, are denoted by v.

[b] Model 1 is tested first against Model 2, and then against Model 3.

Table 13

Alternative Structural Models for Context Utilization Components

	Interactive Model[a]	Comparisons with Model 1		
		χ^2	df	p
1.		--	--	--
4.		.61	2	.74
5.		.94	3	.82

[a] In all models, Components 7 and 8 are regressed on Components 2-4 and 3-4, respectively. Intercorrelations among components are as indicated for Model 1 in Table 12.

Table 14

ACOVS Model for Cognitive Ability Tests[a]

		Factor				
		A	B	C	D	E
	Test Measure	Speed of Closure	Flexibility of Closure	Perceptual Speed	Word Fluency	Fluency of Association
1.	Concealed Words	.52	0	0	0	0
2.	Gestalt Completion	.54	0	0	0	0
3.	Hidden Figures (Power)	0	1.00	0	0	0
4.	Hidden Patterns (Speed)	.64	.32	.41	0	0
5.	Finding A's	0	0	.36	0	0
6.	Finding Identical Pictures	0	0	.90	0	0
7.	Word Endings	0	0	0	.69	0
8.	Word Beginnings	0	0	0	.79	0
9.	Controlled Associations	0	0	0	0	.77
10.	Doubly Constrained Associations	0	0	0	0	.75
11.	Simile Interpretation	0	0	0	0	.49

[a] The model uses 23 parameters to account for 55 correlations. The test of fit yielded $\chi^2_{32} = 43.3$, $p = .09$. Standard errors of parameters averaged .21.

Table 15

Correlations Among Cognitive Ability Factors[a]

	A	B	C	D	E
A. Speed of Closure	1.00				
B. Flexibility of Closure	-.11 ± .22	1.00			
C. Perceptual Speed	.28 ± .24	.12 ± .18	1.00		
D. Word Fluency	.60 ± .23	.39 ± .29	.33 ± .19	1.00	
E. Fluency of Association	.55 ± .21	.32 ± .26	.40 ± .18	.86 ± .11	1.00

[a] Correlation greater than .25 are underscored.

Table 16

Correlations of Reading Components with Cognitive Ability Factors Resulting from the Interbattery Factor Analysis[a]

		Cognitive Ability Factor				
	Component	Speed of Closure	Flexibility of Closure	Perceptual Speed	Word Fluency	Fluency of Association
I.	Letter Encoding Efficiency	-.05	-.10	-.31	-.45	-.25
II.	Perceiving Multiletter Units	-.28	-.14	-.32	-.39	-.38
III.	Decoding Efficiency	-.30	-.09	-.44	-.86	-.57
IV.	Word Recognition Efficiency	-.40	.06	-.56	-.61	-.41
V.	Speed in Applying Context	-.15	.08	-.23	-.41	-.29
VI.	Extrapolating a Discourse Representation to Upcoming Text	.35	.02	.20	.52	.70
VII.	Assignment of Topicalized Antecedent as Referent	-.34	-.08	-.52	-.45	-.22
VIII.	Semantic Integration of Antecedents with a Discourse Representation	.03	.19	-.33	-.01	.21

[a] Correlations having absolute value of .25 or greater are underscored.

Table 17

Validity Coefficients[a]

	Component	Criterion Measure			
		Reading Time For Context	Nelson-Denny Speed	Nelson-Denny Vocabulary	Nelson-Denny Comprehension
I.	Letter Encoding	.17	-.18	-.31	-.20
II.	Perceiving Multiletter Units	.20	-.28	-.30	-.29
III.	Decoding	.70	-.48	-.62	-.68
IV.	Word Recognition Efficiency	.50	-.17	-.35	-.51
V.	Speed in Applying Context	.42	-.03	.00	-.21
VI.	Extrapolating a Discourse Representation	-.51	.37	.47	.59
VII.	Influence of Topicality of Reference	.23	-.17	-.23	-.34
VIII.	Semantic Integration of Antecedents	.41	-.11	.08	.02
	Mult. R	.74	.63	.73	.76
	F (7, 38)	6.48	3.63	6.08	7.50
	Prob.	.000	.000	.000	.000

[a] Correlations of .25 or greater are underscored.

FIGURE CAPTIONS

Figure 1. Categories of reading processes and the nature of their interactions.

Figure 2. Schematic representation of the measurement model for tasks in the word analysis domain. The arrows denote the direction of causation in the model. Squares denote the observed variables (1-10 in Table 2), and circles the components ($\eta_{I}-\eta_{IV}$), including (I) Letter Encoding, (II) Encoding Multiletter Units, (III) Decoding, and (IV) Word Recognition. The model uses 18 parameters to account for 45 correlations. The test of fit yielded $\chi^2_{27} = 38.3$, $p = .073$. Standard errors of parameters averaged .20.

Figure 3. Schematic representation of the measurement model for measures in the discourse analysis domain. Arrows denote direction of causation in the model, and squares denote observed variables (1-6 in Table 4). $\eta_{VII}-\eta_{IX}$ denote the components (VII) Automatic assignment of topicalized antecedent as referent, (VIII) Schematic integration/evaluation of antecedent with discourse representation, and (IX) Exhaustive retrieval of antecedents. $\varepsilon_1-\varepsilon_6$ represent measurement error specific to a single measure.

Chi-square (with 3 degrees of freedom) is 3.17, $p = .37$. A test of independence of the three components yielded $\chi^2_3 = 1.82$, $p = .61$.

Figure 4. Schematic representation of the measurement model developed for measures of context utilization (integrative skills). Arrows denote direction of causation in the model, and squares denote observed variables. (Variables 1-8 are those in Table 6; Variables 9 & 10 correspond to those in Table 2 -- the depth of decoding of high-, and low-frequency words presented in isolation; Variables 11 & 12 correspond to Variables 4 & 3, respectively, in Table 4 -- two measures of time for evaluating antecedents in reading a sentence containing an anaphor.) η_{IV}, η_{V}, η_{VI}, and η_{VIII} denote the components (IV) Word recognition, (V) Speed set in applying context, (VI) Extrapolation of discourse context, and (VIII) Semantic integration within a discourse representation. Measures of Components IV and VIII were included, in order to partial out their involvement in tasks related to the integrative components (V and VI). Chi-square for this measurement model was 45.8, with 42 degrees of freedom; $p = .316$. Standard errors of parameters averaged .17. Only the two significant component intercorrelations are represented in the diagram.

Figure 5. ACOVS model for tasks in the word analysis domain. The arrows denote the direction of causation in the model. Squares denote the observed variables ($\underline{Y}_1$-$\underline{Y}_{10}$) and circles the manifest components. η_I-η_{IV} denote, respectively, the components (I) Encoding letters, (II) Encoding multiletter perceptual units, (III) Phonological decoding, and (IV) Word recognition. ζ_{III} and ζ_{IV} represent unique components; and ε_1-ε_{10} represent measurement error variance specific to a single measure.

Figure 6. Causal model relating two components of discourse processing, (VII) Assignment of topicalized referent and (VIII) Semantic integration of antecedents within a discourse representation, to components of word analysis: (I) Letter recognition, (II) Multiletter unit identification, (III) Decoding, and (IV) Word recognition. In the model, there are direct structural relations between perceptual/decoding components and discourse processing components.

Figure 7. Structural model relating two components of context utilization, (VI) Extrapolating a discourse representation and (V) Speed set in utilizing highly predictive context, to components of word analysis: (I)

Letter identification, (II) Multiletter unit identification, (III) Decoding, and (IV) Word recognition. In this model there are no direct effects of perceptual/decoding components on high-level components.

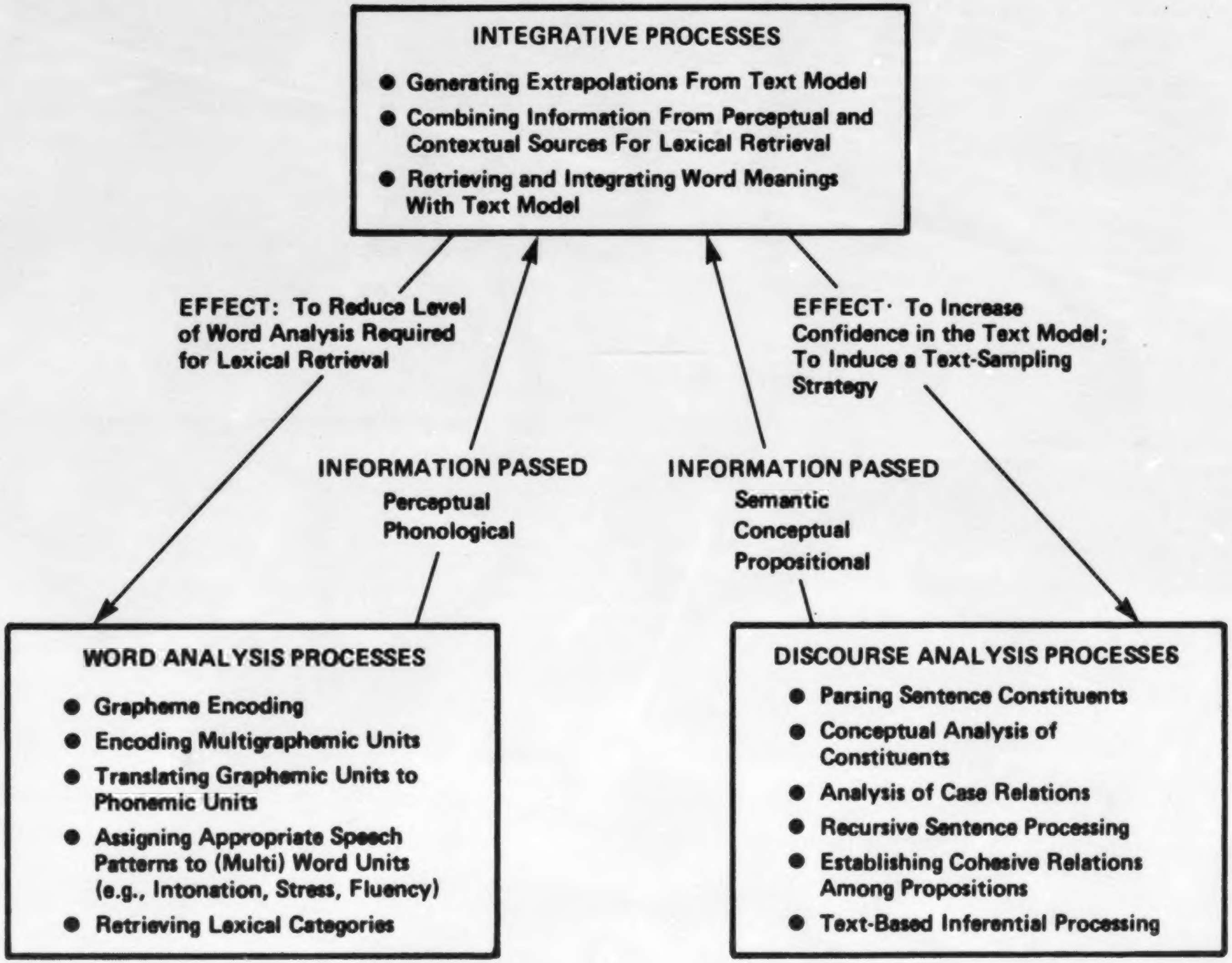
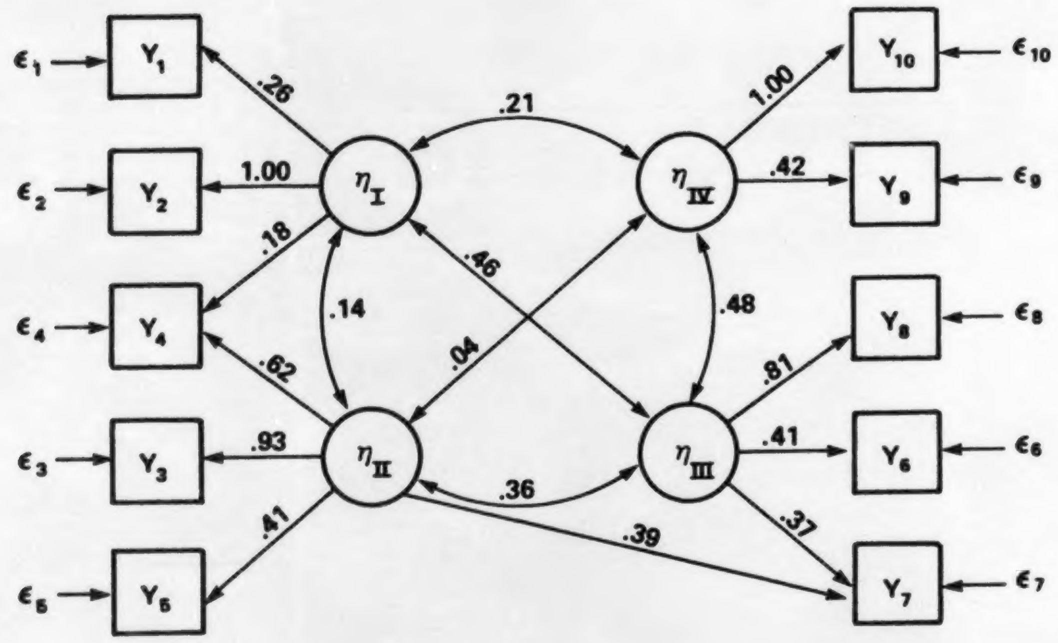

INTEGRATIVE PROCESSES
● Generating Extrapolations From Text Model
● Combining Information From Perceptual and Contextual Sources For Lexical Retrieval
● Retrieving and Integrating Word Meanings With Text Model
EFFECT: To Reduce Level of Word Analysis Required for Lexical Retrieval
EFFECT· To Increase Confidence in the Text Model; To Induce a Text-Sampling Strategy
INFORMATION PASSED
Perceptual
Phonological
INFORMATION PASSED
Semantic
Conceptual
Propositional
WORD ANALYSIS PROCESSES
● Grapheme Encoding
● Encoding Multigraphemic Units
● Translating Graphemic Units to Phonemic Units
● Assigning Appropriate Speech Patterns to (Multi) Word Units (e.g., Intonation, Stress, Fluency)
● Retrieving Lexical Categories
DISCOURSE ANALYSIS PROCESSES
● Parsing Sentence Constituents
● Conceptual Analysis of Constituents
● Analysis of Case Relations
● Recursive Sentence Processing
● Establishing Cohesive Relations Among Propositions
● Text-Based Inferential Processing

Figure 1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ε2
Y2
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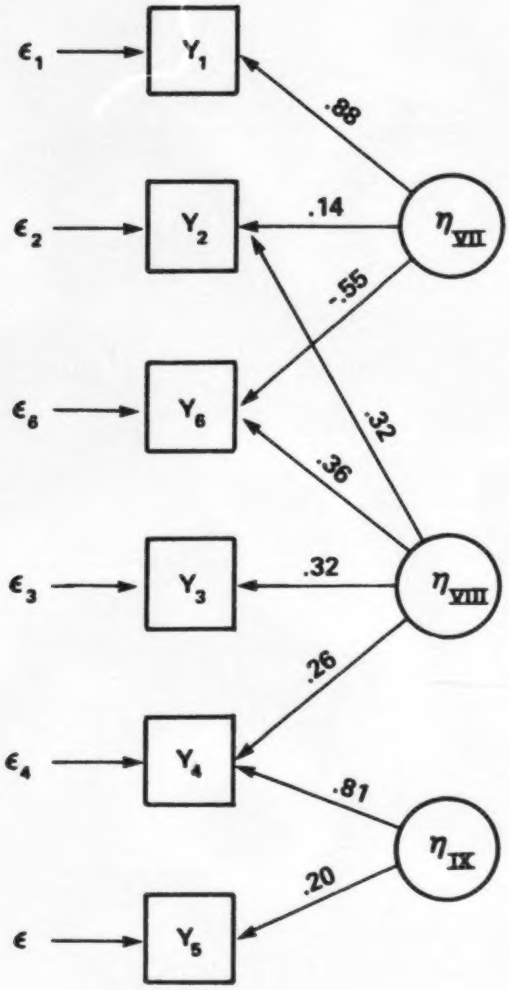
ε4
Y4
.62
ε3
Y3
.93
ε5
Y5
.41
ηI
ηII
.14
.21
.46
.04
.36
.39
ηIV
ηIII
.48
1.00
Y10
ε10
.42
Y9
ε9
Y8
ε8
.81
.41
Y6
ε6
.37
Y7
ε7

Figure 2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ε2
Y2
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ηVII
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ε6
Y6
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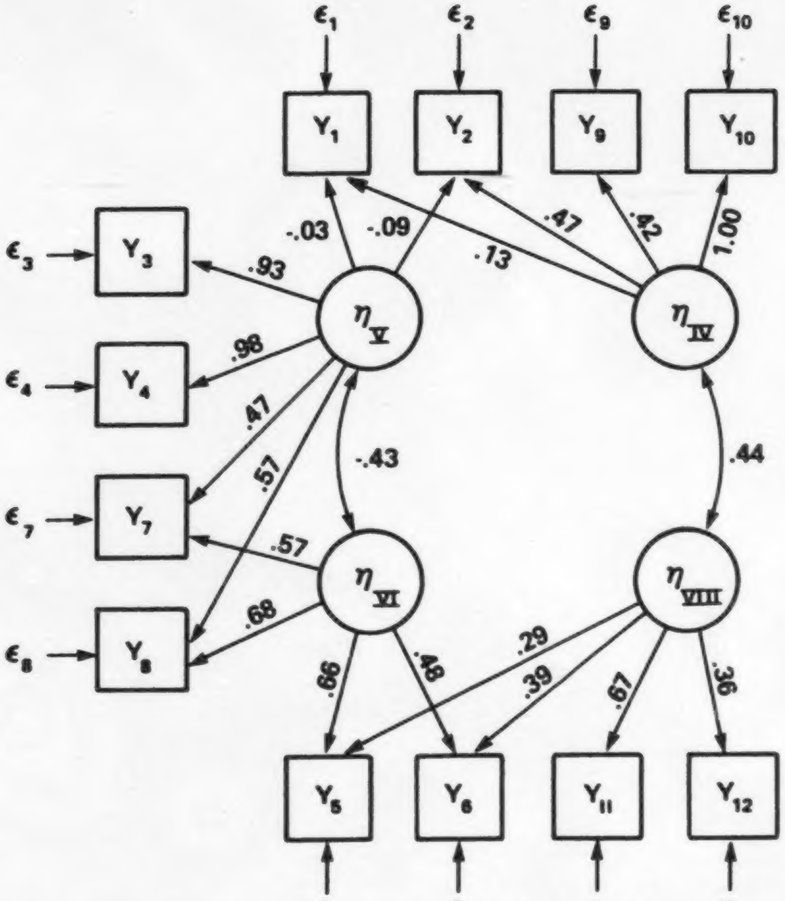
ηVIII
.26
ε4
Y4
.81
ηIX
.20
ε
Y5

Figure 3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ϵ_{10}
Y_1
Y_2
Y_9
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.47
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1.00
ϵ_3
Y_3
.93
η_{V}
η_{IV}
ϵ_4
Y_4
.98
.47
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-.43
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ϵ_7
Y_7
.57
η_{VI}
η_{VIII}
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Y_8
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.39
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.48
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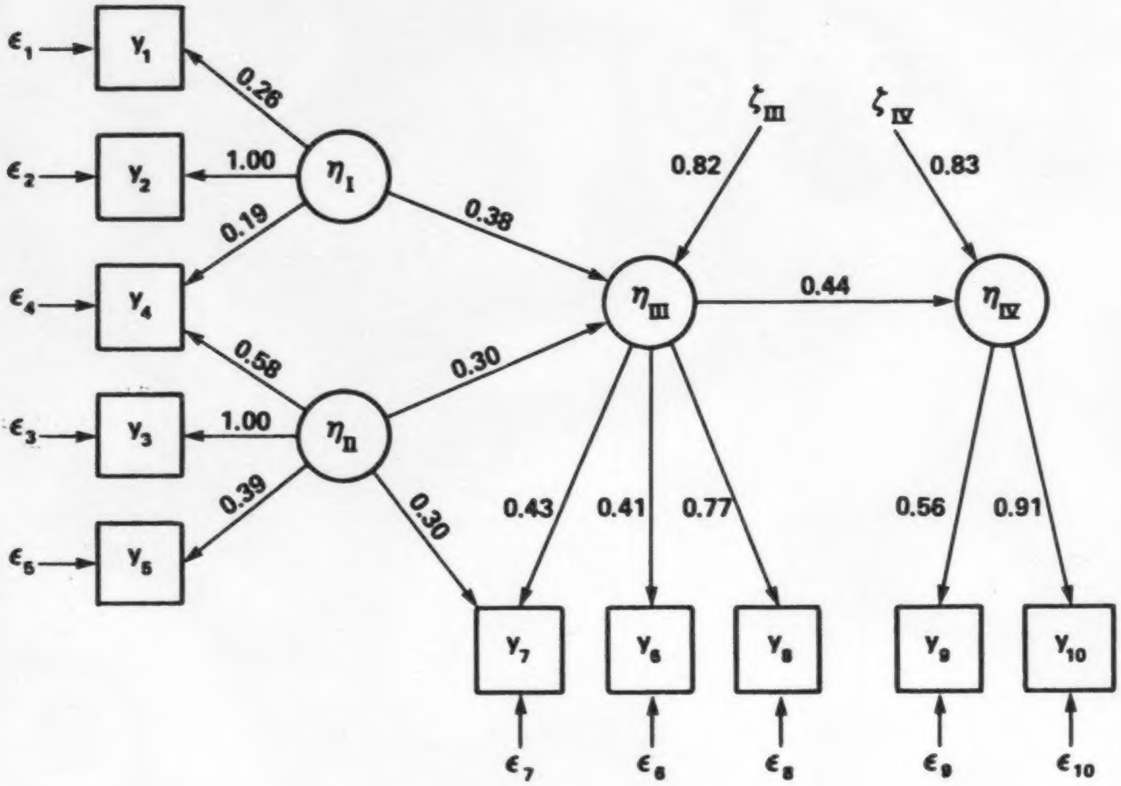
Y_6
Y_{11}
Y_{12}
ϵ_5
ϵ_6
ϵ_{11}
ϵ_{12}

Figure 4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ε3
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Y1
Y2
Y4
Y3
Y5
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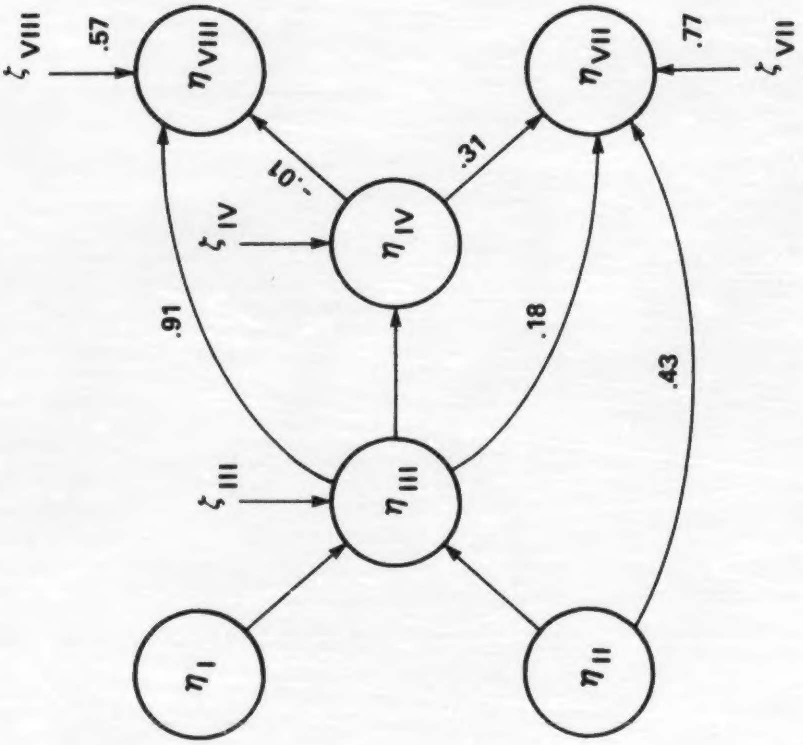
1.00
0.39
η I
η II
0.38
0.30
0.30
ζ III
ζ IV
0.82
0.83
η III
η IV
0.44
0.43
0.41
0.77
0.56
0.91
Y7
Y6
Y8
Y9
Y10
ε7
ε6
ε8
ε9
ε10

Figure 5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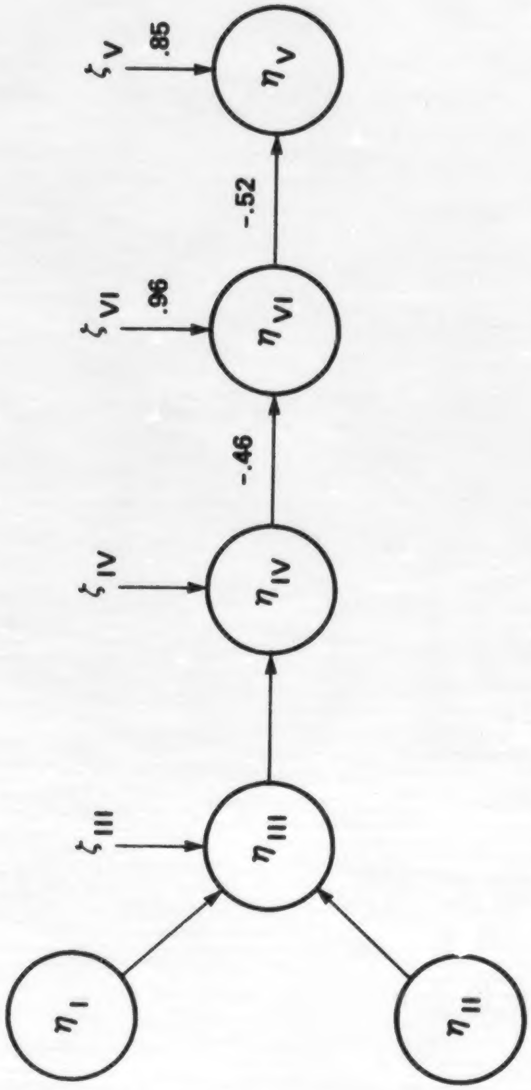
η_{VIII}
η_{VII}
.77
ζ_{VII}
-.01
.31
ζ_{IV}
η_{IV}
.91
.18
.43
ζ_{III}
η_{III}
η_{I}
η_{II}

Figure 6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η_{II}
ζ_{III}
η_{III}
ζ_{IV}
η_{IV}
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ζ_{VI}
.96
η_{VI}
-.52
ζ_V
.85
η_V

Figure 7